School of Computer Sciences

CDS590 – Consultancy Project & Practicum

Final Report

RAPID TECHNIQUE USING RADIOLOGICAL IMAGES TO PREDICT BRAIN TUMOUR

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DECLARATION

"I declare that the following is my own work and does not contain any ***unacknowledged*** work from any other sources. This project was undertaken to fulfil the requirements of the Consultancy Project & Practicum for the Master of Science (Data Science and Analytics) program at Universiti Sains Malaysia".

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ABSTRACT

Exponential growth of data leads to rapid development of data science and analytics. People tends to gain insights of a product or services through data exploration. Academic libraries in university are the organizations that provide reading materials and services for research purposes. A Brain tumour is considered one of the most aggressive diseases, among children and adults. Brain tumours account for 85 to 90 per cent of all primary Central Nervous System (CNS) tumours. Every year, around 11,700 people are diagnosed with a brain tumour. The 5-year survival rate for people with a cancerous brain or CNS tumour is approximately 34 per cent for men and36 per cent for women. Brain tumours are classified as Benign tumours, Malignant tumours, Pituitary tumours, etc. Proper treatment, planning, and accurate diagnostics should be implemented to improve the life expectancy of the patients. The best technique to detect brain tumours is Magnetic Resonance Imaging (MRI). A huge amount of image data is generated through the scans. The radiologist examines these images. A manual examination can be error-prone due to the level of complexities involved in brain tumours and their properties.

The practicum experience has been extremely nice as I had the best mentor and supervisor with me. Both of them supported me in the tough times and are very understanding make me gel with them very easily. Due to pandemic the practicum has been online and even after this, my supervisor has guided me in every aspect. My mentor is also supportive and understands the needs I have had during the practicum and while working on the project. Initially it was tough as I had no idea about how I will execute the plan as I just heard about deep learning and read a article or two. But I started learning and practice can make any perfect or at least closer to being perfect. I would like to thank my supervisor and mentor for kind gesture, support and their belief in me.

The problem statements are the current system has less data with raw format in DICOM based files. The detection glioma is done by manual segmentation which is time taking process leading to detect cancer at later stages. Manual segmentation taking enough time and workforce. Using public dataset and adding it to the available data to make optimal performing model. A deep learning-based framework for detection of a brain

tumour from MRI scans, and survival prediction. Check the performance of the model trained on public dataset and evaluated on USM dataset.

Deep Learning methodologies have been applied in the overall project. From pre-processing to final evaluation, I have used convolutional neural networks and transfer learning in order to find the best performance and evaluate based on their accuracy over training and testing data. The results have been quite exciting, and I did not expect this amount of accuracy when I was initially working on the project. The base model Sequential gave the accuracy of 99% and validation accuracy of 97.6% After applying data augmentation, the accuracy increased in both, with the accuracy of 100% and validation accuracy of 98.50%. Lastly, when transfer learning was applied the mode gave the accuracy of 100% and validation accuracy of 99%.

The lesson I have learned during the entire the deep learning projects are complex and you need ample amount of experience before opting any. The computation power is always a key thing in the deep learning or image classification modelling. Finally, I conclude that the USM dataset is compatible with the public dataset after converting it from raw format to jpg image format. Conversion is also painless process, and you can fine tune the model in order to obtain higher accuracy. The higher the data amount the greater the chances of your model performance.

Keywords: *Brain Tumour, MRI, Practicum, Project, Accuracy, Deep Learning, Validation, Sequential, Transfer Learning*

ABSTRAK

Pertumbuhan eksponen data membawa kepada perkembangan pesat sains data dan analitik. Orang ramai cenderung untuk mendapatkan cerapan tentang produk atau perkhidmatan melalui penerokaan data. Perpustakaan akademik di universiti adalah organisasi yang menyediakan bahan bacaan dan perkhidmatan untuk tujuan penyelidikan. Tumor otak dianggap sebagai salah satu penyakit yang paling agresif, di kalangan kanak-kanak dan orang dewasa. Tumor otak menyumbang 85 hingga 90 peratus daripada semua tumor utama Sistem Saraf Pusat (CNS). Setiap tahun, kira-kira 11,700 orang didiagnosis dengan tumor otak. Kadar kelangsungan hidup 5 tahun untuk orang yang mempunyai otak kanser atau tumor CNS adalah kira-kira 34 peratus untuk lelaki dan 36 peratus untuk wanita. Tumor otak dikelaskan sebagai Tumor benigna, Tumor malignan, Tumor pituitari, dsb. Rawatan yang betul, perancangan, dan diagnostik yang tepat harus dilaksanakan untuk meningkatkan jangka hayat pesakit. Teknik terbaik untuk mengesan tumor otak ialah Pengimejan Resonans Magnetik (MRI). Sejumlah besar data imej dijana melalui imbasan. Pakar radiologi memeriksa imej-imej ini. Pemeriksaan manual boleh terdedah kepada ralat disebabkan oleh tahap kerumitan yang terlibat dalam tumor otak dan sifatnya.

Pengalaman praktikum sangat bagus kerana saya mempunyai mentor dan penyelia terbaik bersama saya. Kedua-dua mereka menyokong saya dalam masa sukar dan sangat memahami membuatkan saya geli dengan mereka dengan mudah. Disebabkan pandemik, praktikum telah dijalankan dalam talian dan selepas ini, penyelia saya telah membimbing saya dalam setiap aspek. Mentor saya juga menyokong dan memahami keperluan yang saya ada semasa praktikum dan semasa menjalankan projek. Pada mulanya ia adalah sukar kerana saya tidak tahu bagaimana saya akan melaksanakan rancangan itu kerana saya baru mendengar tentang pembelajaran mendalam dan membaca satu atau dua artikel. Tetapi saya mula belajar dan berlatih boleh membuat apa-apa yang sempurna atau sekurang-kurangnya lebih dekat untuk menjadi sempurna. Saya ingin mengucapkan terima kasih kepada penyelia dan mentor saya atas isyarat baik, sokongan dan kepercayaan mereka terhadap saya.

Pernyataan masalah adalah sistem semasa mempunyai kurang data dengan format mentah dalam fail berasaskan DICOM. Pengesanan glioma dilakukan secara manual segmentasi iaitu proses mengambil masa yang membawa kepada pengesanan kanser

pada peringkat seterusnya. Pembahagian manual mengambil masa dan tenaga kerja yang mencukupi. Menggunakan set data awam dan menambahkannya pada data yang tersedia untuk menjadikan model berprestasi optimum. Rangka kerja berasaskan pembelajaran yang mendalam untuk pengesanan tumor otak daripada imbasan MRI, dan ramalan kelangsungan hidup. Semak prestasi model yang dilatih pada set data awam dan dinilai pada set data USM.

Metodologi Pembelajaran Dalam telah digunakan dalam keseluruhan projek. Daripada pra-pemprosesan kepada penilaian akhir, saya telah menggunakan rangkaian saraf konvolusional dan pembelajaran pemindahan untuk mencari prestasi terbaik dan menilai berdasarkan ketepatannya terhadap data latihan dan ujian. Hasilnya agak menarik, dan saya tidak menjangkakan jumlah ketepatan ini semasa saya mula-mula mengusahakan projek itu. Model asas Sequential memberikan ketepatan 99% dan ketepatan pengesahan 97.6% Selepas menggunakan penambahan data, ketepatan meningkat dalam kedua-duanya, dengan ketepatan 100% dan ketepatan pengesahan 98.50%. Akhir sekali, apabila pembelajaran pemindahan digunakan mod memberikan ketepatan 100% dan ketepatan pengesahan 99%.

Pelajaran yang saya pelajari semasa keseluruhan projek pembelajaran mendalam adalah rumit dan anda memerlukan pengalaman yang mencukupi sebelum memilih mana-mana. Kuasa pengiraan sentiasa menjadi perkara utama dalam pembelajaran mendalam atau pemodelan klasifikasi imej. Akhir sekali, saya membuat kesimpulan bahawa dataset USM serasi dengan dataset awam selepas menukarnya daripada format mentah kepada format imej jpg. Penukaran juga merupakan proses yang tidak menyakitkan, dan anda boleh memperhalusi model untuk mendapatkan ketepatan yang lebih tinggi. Lebih tinggi jumlah data, lebih besar peluang prestasi model anda.

Kata Kunci: Tumor Otak, MRI, Praktikum, Projek, Ketepatan, Pembelajaran Mendalam, Pengesahan, Berurutan, Pembelajaran Pemindahan

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1. CHAPTER 1

INTRODUCTION

1.1. Organization Background

University Sains Malaysia (USM) which formerly known as Universiti Pulau Pinang is the second university established in Malaysia during 1969. Initially, USM was located at Malayan Teachers' Training College, Bukit Gelugor. In 1971, USM moved to current 416.6-hectare site at Minden which is around 9.7km away from Georgetown. The courses available in USM ranges from Applied Sciences, Natural Sciences, Pharmaceutical Sciences, Health Sciences, Social Sciences, Science and Technology, Education and Humanities. These courses offer at undergraduate and postgraduate levels which involved 30 000 students from 17 academic schools in main campus at Penang Island, 6 schools in Engineering Campus at Nibong Tebal and 3 schools in Health Campus at Kubang Kerian, Kelantan. USM implemented school system instead of faculty system is to ensure USM students are multi-disciplined from the exposure to other fields of study from other schools and encourage students participate actively in extra-curricular activities of societies and clubs available.

Meanwhile, USM consists of 17 research centres specialized in medicine and dentistry, science and technology, Islamic development and management studies, policy research and international studies, archaeology, and molecular medicine which provides consultancy, advisory services, and testing for industry under scope of USAINS Holdings Sendirian Berhad which is the University commercial arm. USM was recognized as a Research-Intensive University by Ministry of Higher Education Malaysia (MOHE) in 2007 which offers wide range of educational and research opportunities for the staffs and students. USM was the first university in Malaysia that was selected by the government in participating Accelerated Programme for Excellence (APEX) which is a fast-track program which aids tertiary institutions accomplish word-class status (USM, 2016).

The school of dental sciences was established in the year 1998 located at USM, Kelantan branch, now known as Health Campus, situated in Kubang Kerian. The school has more than 23 years of rich history in academics, research, innovation, and services.

1.2. Domain Background

Individuals have begun to centre on the unused possibilities of information science and analytics in contributing logical information due to the blast of information. The advancement and progress of information in information science and analytics lead to the application of demonstrating and visualizing information within the investigation of approaches, and extraction of backgrounds and patterns.

A Brain tumour is considered one of the most deadly and Fatal diseases, among every age group. Brain tumours account for the majority of all primary Central Nervous System (CNS) tumours. Every year, around 11,700 people are diagnosed with a brain tumour. The 5-year survival rate for people with a cancerous brain or CNS tumour is approximately 34 per cent for men and 36 per cent for women. Brain tumours are classified as Benign tumours, Malignant tumours, Pituitary tumours, etc. Proper treatment, planning, and accurate diagnostics should be implemented to improve the life expectancy of the patients.

Brain tumours can be classified into two types: benign (non-cancerous) and malignant (cancerous). The malignant tumour scan quickly spread to other tissues in the brain and lead to worsening the patient's condition (Joshi, 2013). When most of the cells are old or damaged, they are destroyed and replaced by new cells. if damaged and old cells are not eliminated with generating the new cells, it can cause problems. The production of additional cells often results in the formation of a mass of tissue, which refers to the growth or tumour. Brain tumour detection is overly complicated and difficult due to the size, shape, location, and type of tumour in the brain. Diagnosis of brain tumours in the preliminary stages of the tumour's start is difficult because it cannot accurately measure the size and resolution of the tumour (Aboody KS, 2000).

However, if the tumour is diagnosed and treated early in the tumour formation process, the chance of patient's treatment is extremely high. Therefore, the treatment of tumour depends on the timely diagnosis of the tumour (Shah, 2013). The diagnosis is usually done by a medical examination, with computer tomography or magnetic imaging. MRI imaging is a method that provides accurate images of the brain and is one of the most common and important methods for diagnosing and evaluating the patient's brain. In the field of Medical Detection Systems (MDS), MRI images provide better results than

other imaging techniques such as Computed Tomography (CT), due to their higher contrast in soft tissue in humans (Poonam, 2013).

The proposed technique has used CNN to identify and categorize the tumour from brain images of the brain. The main difference between the main channel of the neural network with the normal neural network is that it is able to extract the feature automatically and locally from each image (Graeser, 2008). These types of networks consist of neurons with weights and biases that can be learned (Gonalves, 2015).

Due to the results of CNN on the dataset, in order to improve the proposed method. Machine learning algorithm is used to feature extraction. The algorithm used was the flattening algorithm applied on data set, and then the images are applied to the CNN. The results showed that the proposed method has been successful. The purpose of extracting the property before applying to the CNN is that in some images fatty masses are considered as tumours, or in some images the tumour is mistakenly considered to be fat and should have increased medical error. Extracting the attribute initially and before applying the CNN leads to improved network accuracy and increased accuracy.

1.3. Problem Statement

A brain tumour is characterized as the anomalous development of cells inside the brain or central spinal canal. A few tumours can be cancerous in this way they got to be identified and cured in time. The precise cause of brain tumours isn't clear and not one or the other is the precise set of indications characterized, in this way, individuals may be suffering from it without realizing the peril. Essential brain tumours can be either threatening (contain cancer cells) or kind (don't contain cancer cells).

A brain tumour is a cancerous or noncancerous mass or growth of abnormal cells in the brain. Gliomas are the most prevalent type of brain tumour that arise from glial cells. Gliomas are classified as glioblastoma (GBM/HGG), or lower grade glioma based on the pathological assessment of the tumour (LGG). Glioblastoma is one of the most deadly and aggressive brain tumours in humans. Gliomas contain various heterogeneous histological sub-regions, including peritumoral oedema, a necrotic core, an enhancing, and a non-enhancing tumour core. Magnetic resonance imaging (MRI) is commonly used in radiology to portray the phenotype and intrinsic heterogeneity of

gliomas, since multimodal MRI scans, such as T1-weighted, contrast enhanced T1-weighted (T1Gd), T2 -weighted, and Fluid Attenuation Inversion Recovery (FLAIR) images. It provides complementary profiles for different sub-regions of gliomas. In addition, the accurate and robust predictions of overall survival, using automated algorithms, for patients diagnosed with gliomas can provide valuable guidance for diagnosis, treatment planning, and outcome prediction The CT picture obtained from the CT machine gives a two-dimension cross-sectional of the brain. In any case, the picture obtained did not extract the tumour from the picture. Hence, picture preparation is required to decide the seriousness of the tumour depending on the measure.

- The current system has less data with raw format in DICOM based files.
- The detection glioma is done by manual segmentation which is time taking process leading to detect cancer at later stages.
- Manual segmentation taking enough time and manpower.

1.4. Research Questions

The research question assists in controlling the approach of research. The research questions for this project are:

- How these files (DICOM) can be converted to fit into machine learning model.
- Predicting the tumour rapidly to be used by the surgeon for patients.
- How the prediction of glioma can help the surgeon in robust diagnosis.

1.5. Objectives of Project

The objective of this project is:

- Using public dataset and adding it to the available data to make optimal performing model.

  As the dataset I got from my mentor is very less. For deep learning and image classification projects, the more the amount of data the better the model will be. As it learns from the images to predict future issues. During the midterm presentation, Prof Dr Anousha, the panellist advice to use public dataset as the dataset I was having till then was very less. The advice was to add increased images to the dataset and focus on researching and experimenting with the deep learning methods.

- A deep learning-based framework for detection of a brain tumour from MRI scans, and survival prediction.

  As we know, in machine learning, there is a subsidiary of machine learning called deep learning which is helpful for image classification and deep learning projects. It has vast amounts of models, pretrained too, which can be used in the detection of brain tumour (in this case). Convolutional Neural Network (CNN) is considered to be the best model for these types of deep learning applications.

- Check the performance of the model trained on public dataset and tested on USM dataset.

  Again, the panellist advice to not use the USM server for deployment as the dataset I will be using after deployment will be of the patients. These data will be in the DICOM format which contains various information, and in case of data breach, it is a matter of concern. An, it's also a kind research work as I am testing the USM data on public dataset which is going to be crucial in the coming future.

1.6. Benefit of Project

Brain tumour detection at preliminary stages can increase the chances of the patient's recovery after treatment. In the last decade, I have noticed a substantial development in the medical imaging technologies, and they are now becoming an integral part in the diagnosis and treatment processes.
Implementation of this project will lead to rapid detection of brain tumours. This will help in the surgeons to start the diagnosis at preliminary stages. The chances of patient's recovery are more likely to happen when the tumour is in early stage.

The advantages of the convolutional neural network are the fact that it provides optimal accuracy of segmentation. However, this is at the cost of computational load (M Angulakshmi, 2017). With advances in computation, the implementation of convolutional neural networks and refinement of the structural segmentation of brain tumours can be enhanced.

Depending on the better performance of the proposed model, this helps in developing computer-aided system for early detection of brain tumours and helps the doctors to diagnose the patients better.

2. CHAPTER 2

RELATED WORKS

2.1. Introduction

A brain tumour could be a collection of irregular cells within the brain. A tumour may lead to cancer, which could be a major driving cause of death and dependable for around 11% of all passings around the world. The cancer frequency rate is developing at an alarming rate within the world. So, location of the tumour is exceptionally critical in prior stages.

Diagnosing brain cancer starts with taking an exhaustive individual and family medical history, including indications and hazard components for brain cancer. The diagnostic handle moreover incorporates completing a careful physical and neurological exam. A neurological aid assesses the brain and apprehensive framework and such functions as reflexes, sensation, development, adjust, readiness, coordination, vision, and hearing.

Extraordinary knowledge and experience on radiology are required for accurate tumour discovery in restorative imaging. The brain tumour could be a risk level depending upon the combination of components just like the sort of tumour, its position, its size, and its state of development.

2.2. Related Works

(Mustaqeem, Javed, & Fatima, 2012), benign additionally may be grown as malignant which includes cancerous cells. Malignant is a hastily developing tumour that's invasive and life-threatening. It is likewise referred to as mind most cancers for the reason that malignant comprise cancerous cells that could damage any close by cell.

(P. Natarajan, 2012) states that Primary mind tumours encompass any tumour that begins off evolved withinside the mind. Primary mind tumours can begin from mind cells, the membranes across the mind (meninges), nerves, or glands. Tumours can without delay damage mind cells. They also can harm cells via way of means of generating inflammation, putting strain on different elements of the mind, and growing

strain in the skull. A metastatic brain tumour is a cancer that has spread from elsewhere in the body to the brain.

The traditional definition of mind tumour consists of neoplasms originating from mind parenchyma in addition to from meninges or even tumours of the pituitary gland or of osseous intracranial shape that could circuitously have an effect on mind tissues (Ramasamy & Anandhakumar, 2011).

However, maximum of the method used is greater on MRI modality in comparison to CT snap shots due to the fact it's far better resolutions. CT snap shots of human frame elements assist clinical docs in diagnosing ailments like mind tumours, colon most cancers, lung most cancers and so forth. However, it's far pretty hard to attain the vital capabilities withinside the snap shots due to the fact it's far confined via way of means of the picture processing stage and additionally the doctor’s experience expressed (Nanthagopal & Sukanesh, 2011).

(X. Zang, 2010) Histogram includes a depth cost of 0-255. The 0 cost is the darkest component even as the 255 changed into the white or the brightest side. Using the histogram evaluation method used the combination Gaussian clear out for the extracted component pixel depth.

Brain tumour is a life-threatening issue and affects the functions of a normal human body. For proper diagnosis and effective treatment, it is important to detect the brain tumour in the early stage. Digital image processing plays a significant role in analyzing the medical images. The proper diagnosis of a brain tumour is difficult because of the complex structure of tumours in terms of their size, shape, and existence. Manual detection of brain tumours by radiologists may be wrong and results can vary from one radiologist to another and may not necessarily ensure proper diagnosis (Rania Hussien Al-Ashwal, 2011).

(Fausto Milletari, 2016) In this research work, the Convolutional Neural Network (CNN) was implemented, which drives an overall accuracy of 91.3% and a recall of 88%, 81% and 99% in the detection of meningioma, glioma, and pituitary tumour respectively. Deep learning architecture by leveraging 2D convolutional neural networks for the classification of the several types of brain tumour from MRI image slices. In this paper techniques like data acquisition, data pre-processing, pre –model,

model optimization and hyper parameter tuning are applied. Moreover the 10-fold cross validation was performed on the complete dataset to check for the generalizability of the model.

(Dogantekin, 2019) The method applied in this paper is based on Hough voting, a strategy that allows for fully automatic localization and segmentation of the anatomies of interest. It also used learning techniques-based segmentation method, which is robust, multi-region, flexible and can be easily adapted to different modalities. Different amount of training data and different data dimensionality (2D, 2.5D and 3D) are applied in predicting the final results. Convolutional neural networks, Hough voting with CNN, Voxel-wise classification and Efficient patch-wise evaluation through CNN are used in analyzing the image.

In this paper a Brain Cancer Detection and Classification System have been developed with the use of ANN. (Gonge, 2014) The image processing techniques such as histogram equalization, image segmentation, image enhancement, and feature extraction have been used. The proposed approach using ANN as a classifier for classification of brain images provides a good classification efficiency as compared to other classifiers. The sensitivity, specificity and accuracy are also improved. The proposed approach is computationally effective and yields good result.

(Kamel, 2020) The brain is an essential organ in the human body which control and coordinates the tasks conducted by the other parts of the body. It is primarily the control centre of the central nervous system and is responsible for performing the daily voluntary and involuntary activities in the human body. The tumour is a fibrous mesh of unwanted tissue growth inside our brain that proliferates in an unconstrained way. Prevent and to cure the tumour, radiologists widely use magnetic resonance imaging (MRI) to analyse stages of brain tumours. The result of this analysis reveals the presence of the brain tumour.

The typical method to detect brain tumours is Magnetic Resonance Imaging (MRI) scans. The abnormal tissue growth in the brain can be identified by the MRI. CNN is believed one of the best methods for analyzing the image dataset. The CNN predicts by reducing the size of the image without losing the details required for making predictions. The ANN shows low accuracy compared to the CNN but can be improved

by providing more data for training the model. CNN continues to be the better technique than the ANN for the work done by P Prasanth (Prasanth, 2021). In the paper, Brain Tumor Detection Using Deep Neural Network and Machine Learning Algorithm, the results of CNN using the proposed method (i.e., combining the feature extraction algorithm and CNN-SoftMax) on dataset. The accuracy of proposed method increased to 99.12% on the test data, which is an improvement compared to the traditional CNN. (Teshnehlab, 2019)

(Sahu, 2022) In this work involves the semantic segmentation of the MRI. The results of this paper help to detect the presence of tumours inside the brain. This work utilizes an optimal framework UNet. UNet has two pathways in its architecture - the encoder (involves the contraction) in the first half and the decoder (involves the expansion) in the second half. The paper uses the dataset from The Cancer Imaging Archive website. The model is very well compiled with the Adams optimizer. The model implemented in this paper has an accuracy of 96.71% with the test datasets.

(S. N. Shivhare, 2019) presented a fully automated strategy for segmentation of brain tumour by making use of parameter free K-means clustering algorithm and mathematical morphological operations like dilation and ho1e fi1ling. The proposed strategy is used on training dataset of Brats 2015. The tumour segmented using the presented approach is correlated with the ground truth result available in the dataset. The obtained results showed 75% of Dice Similarity Coefficient (DSC) with the available ground truth.

(Jagan, 2018) presented a novel approach for segmentation of tumour where acquired image is pre-processed using anisotropic filter. Then FCM approach and improved Expectation Maximization (EM) approach are applied to perform initial segmentation. Next, superior segmentation is performed using suggested approach. The work of the suggested technique is correlated with FCM clustering approach and improved EM approach in context of segmentation accuracy. The proposed approach resulted in average 97.98% segmentation accuracy calculated over 10 patients and outperforms the FCM clustering and improved EM methods.

(P. P. R. Filho, 2019) presented an Optimum Path Snakes (OPS) based adaptive and parameter free algorithm for segmenting medical images. Initially, pre-processing is

done to extract the features such as texture using HU moments, Gray Level Co-occurrence Matrix (GLCM), Human Density Analyse (HDA) and statistical moments. Then, segmentation is done using OPS method. The performance evaluation metrics such as Hausdorff distance (HD), Dice Coefficient (DC), and processing time are calculated. For lung segmentation, the proposed approach is compared with the existing vector field convolution method and gradient vector flow method. For brain segmentation, the proposed approach is compared with watershed method, region growing method and Level Set algorithm based on Coherent Propagation Method (LSCPM). The proposed technique outperforms the existing methods. This approach is not application specific and is not limited to particular image type.

(J. R. Dandu, 2019) presented a Statistical Region Merging (SRM) and Back Propagation Neural Network (BPNN) classification-based approach for segmentation of pancreatic and brain tumour. In this approach, first the image is pre-processed using Decision Based Couple Window Median Filter (DBCWMF) method. Next, segmentation is conducted using SRM. Then, features are extracted using Cat Swarm Optimization (CSO) and Scale Invariant Feature Transform (SIFT) techniques. Then, BPNN classifier is used for classification. In the proposed approach, DBCWMF performs better than median and PGPD filter and BPNN classifier performs better than Artificial Neural Network (ANN) and AdaBoost classifier. The suggested method outperforms the existing methods in context of Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR), accuracy, precision, specificity and recall performance evaluation metrics.

(Rani, 2018) suggested a nove1 technique for detection of brain tumour in preliminary stages. In the proposed approach, acquired brain MRI images are pre-processed using Optimized Kernel Possibilistic C-means Method (OKPCM). Then, image enhancement is done using adaptive Double Window Modified Trimmed Mean Filter (DWMTMF). Finally, image segmentation is performed using region growing technique. The suggested OKPCM technique is correlated with K-means, CLOPE and FCM techniques in context of processing time and accuracy. The proposed OKPCM results in higher accuracy as compared to other methods. But, in context of processing time KMeans method is faster. The proposed DW-MTMF filter is compared with the mean, BM3D and median filter in terms of MSE and PSNR. DW-MTMF performs better than the

other filters. The proposed region growing segmentation method is compared with K-Nearest Neighbours (KNN), edge detection and fuzzy techniques in terms of accuracy and error rate. The region growing approach outperforms the other methods.

(J. Amin, 2018) presented an unsupervised clustering approach for brain tumour detection. Initially, lesion enhancement is conducted using histogram matching method. Then, the lesion is segmented using an unsupervised clustering (C) method with C=5 clusters. Then, feature extraction is conducted where four texture features Gabor Wave1et Features (GWF), Histogram of Oriented Gradient (HOG), Local Binary Pattern (LBP), and Segmentation based Fractal Texture Analysis (SFTA) are extracted. The fused feature vector is then created by fusing these four features. Then tumour classification is done using Random Forest (RF) classifier. The proposed approach is evaluated on BraTS 2012, BraTS 2013, BraTS 2014, BraTS 2015 datasets and is compared with the techniques like Conditional Random Fields (CRF), deep Convolutional Neural Networks (CNN), CNN, Otsu clustering, U-net based fully CNN, random decision forest based, 3D CNN in context of Area Under Curve (AUV), sensitivity, accuracy, specificity, Negative Predictive Value (NPV) and Positive Predictive Value (PPV) as performance measures. The proposed approach outperforms the existing methods.

(A. R. Raju, 2018) presented a Bayesian fuzzy clustering-based approach for segmenting and classifying brain tumour. In the suggested approach, segmentation is conducted using Bayesian fuzzy clustering method. Then, the scattering transform, the wavelet transforms, and the information theoretic measures are used for the extraction of features. Finally, classification is done using multi–Support Vector Neural Network (SVNN) classifier in which weights are trained using Harmony Crow Search (HCS) optimization method. The performance of the suggested Bayesian HCS multi SVNN approach is evaluated against the existing KNN, Neural Network (NN), multi–Support Vector Machine (SVM), multi SVNN techniques using sensitivity, accuracy, and specificity as performance metrics. The proposed approach excels the existing methods.

(Emmanuel, 2018) presented a fused feature Adaptive Firefly Backpropagation Neural Network (AFBNN) approach for brain tumour detection. Initially, the image is pre-processed using the average filter. Then, the texture features like orientation, locality and frequency are extracted using the Gabor Wavelet technique. Then, the most relevant

features are selected using Kernel Principal Component Analysis (KPCA). Notable information is provided through feature fusion using Gaussian Radial Basis Function (GRBF). Finally, classification is done using AFBNN classifier. The proposed approach is validated using BRATS 2015 dataset. The proposed approach is evaluated for performance using sensitivity, accuracy, and specificity as performance metrics against the Naïve Bayes, SVM and Linear Discriminate Analysis (LDA) classifiers. The proposed approach excels the other classifiers.

(Mandava, 2018) presented a multi-phase technique for segmenting the multisequence image of brain tumour. The proposed technique consists of three stages. In the initial stage, random wa1ks technique is used for modelling the information. In the second stage, information is fused using weighted averaging approach. The last stage involves the extraction of visual objects using Information Theoretic Rough Sets (ITRS). Brain tumour dataset of MICCAI is used for evaluating the proposed strategy. The suggested method is correlated with the simple averaging and Principal Component Analysis (PCA) fusion techniques. The performance of the presented strategy is evaluated using DICE metric and resulted in average DICE accuracy of 0.7 for high grade tumour and 0.63 for low grade tumour.

(K. K. K, 2018) presented an efficient approach for detection of brain tumour. Initia1ly, the acquired MRI image is denoised by using Poisson Unbiased Risk Estimator- Linear Expansion of Thresholds (PURE-LET) transform. Next, the features are extracted using a combined technique of Modified Multi-Texton Histogram (MMTH) and Multi-Texton Microstructure Descriptor (MTMD). Then, the performance is compared using a combination of two another technique of feature extraction – Gray Level Run Length Matrix (GLRLM) and GLCM. Finally, the features so extracted are used to train the classifiers such as KNN, SVM and Extreme Learning Machine (ELM) which are then used for image classification. The result of the suggested approach is correlated by using three classifiers in context of accuracy, specificity, and sensitivity as performance evaluation metrics. The precision of proposed strategy with KNN classifier is 80%, with SVM classifier is 95% and with ELM classifier is 91%. Thus, the proposed approach with SVM classifier shows higher accuracy than the remaining two classifiers.

(S. J. Nanda, 2018) presented a hybrid K-means Galactic Swarm Optimization (GSO) approach with Otsu’s entropy as a fitness function for the purpose of determining the

position, form, and shape of brain tumour. The proposed approach is correlated with the existing approaches such as K-means, GSO and Real Coded Genetic algorithm for performance using the Normalized Root Mean Square Error (NRMSE), PSNR, Structured Similarity Index Measure (SSIM), Otsu's measure and computational time as the performance measures. The suggested technique excels the existing approaches for all the performance measures taken except the computational time. The presented approach is computationally more expensive than the existing techniques.

(A. Vishnuvarthanan, 2017) presented an automated method for segmenting the tumour and tissues which is based on the clustering and optimization techniques. Skull stripped brain MRI image is taken as input to this approach. Contrast limited adaptive histogram equa1ization method is used to pre-process the skull stripped image. Then, Modified Fuzzy K-means (MFKM) technique is adopted to conduct the clustering. Next, optimum value of threshold is identified using Bacteria Foraging Optimization (BFO) algorithm. The result of MFKM method is re-evaluated using the identified threshold value. The proposed approach is correlated with the existing MFKM, Particle Swarm Optimization (PSO) based FCM and conventional FCM techniques. The work of the suggested method is assessed using PSNR, MSE, sensitivity, Jaccard Index (JI), specificity, Dice Overlap Index (DOI), storage requirement and computational time as performance metrics.

(Wongthanavasu, 2017) presented a segmentation technique which makes use of cellular automata and improved tumour cut technique. In the proposed strategy, initially an image is transformed to the target featured image using GLCM based Cellular Automata (GLCM-CA). Then, the segmentation is conducted using improved tumour cut method. The proposed approach is evaluated on BraTS 2013 dataset for performance evaluation using DC, sensitivity, specificity, PPV as the performance evaluation metrics. The suggested method is correlated with the state-of-the art techniques which are conducted on the same dataset. The suggested approach excels the state-of-the art approaches.

(G. Vishnuvarthanan, 2016) presented an unsupervised learning technique with clustering strategy for identifying and segmenting the brain tumour. The brain MR image is initially skull stripped using Brain Extraction Tool (BET) and Region of Interest (ROI) based brain mask. Next, initial clustering, dimensionality reduction and

prototype preparation is conducted using Self Organizing Map (SOM). Then, the segmentation is performed using Fuzzy KMeans (FKM) method. The efficiency of the suggested approach is assessed by utilizing MSE, PSNR, DOI, JI, storage requirement and computational time against the conventional FCM algorithm. The proposed SOM-FKM technique excels the convention FCM approach.

(Y. Zhang) presented a Multilayer Perceptron (MLP) approach for detection of pathological brain. In the first step, feature extraction is conducted where 12 Fractional Fourier Entropy (FRFE) features are extracted. In the next step, MLP classifier is used for classification. Optimal hidden neuron number is determined using pruning technique. Three pruning techniques are compared – Kappa Coefficient (KC), Bayesian Detection Boundaries (BDB) and Dynamic Pruning (DP). The training of weights and biases is conducted using Adaptive Real- Coded Biogeography Based Optimization (ARCBBO). The obtained results depicted that the combination of FRFE, KC, MLP and ARCBBO obtained better average accuracy 99.53%. The proposed approach is compared with SVM, and native Bayesian classifiers and it outperforms the other two classifiers.

2.3. Data Science & Analytics Techniques

2.3.1. Artificial Intelligence

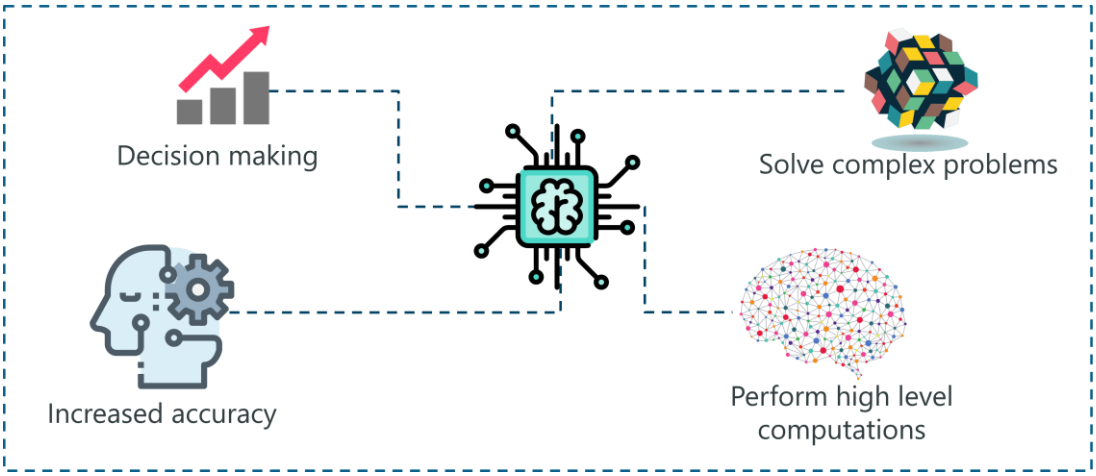

Figure 1: Artificial Intelligence

If I were to name a technology that completely revolutionized the 21st century, it would be Artificial Intelligence. AI is a part of our everyday life and that is why I think it's important we understand the different concepts of Artificial Intelligence.

Artificial intelligence (AI) is a simulation of human intelligence processes by machines, especially computer systems, and can even imitate human behaviour. Its applications include computer vision, natural language processing, robotics, and speech recognition. Benefits of using AI include improving the customer experience, reducing time to market, developing sophisticated products, achieving cost optimization, increasing employee productivity, and improving employee's productivity operational efficiency.

Machine learning (ML) is a subset of AI that is programmed to think for yourself, engage in social interactions, learn latest information from the data provided, and adapt and enhance on the experience. The training time for deep learning (DL) techniques is longer than that for machine learning methods, but the former is more accurate. DL is automatic, so unlike ML, it does not require a lot of domain mastery to get the desired outcomes.

Artificial Intelligence can also be defined as the development of computer systems that are capable of performing tasks that require human intelligence, such as decision making, object detection, solving complex problems and so on.

2.3.2. Deep Learning

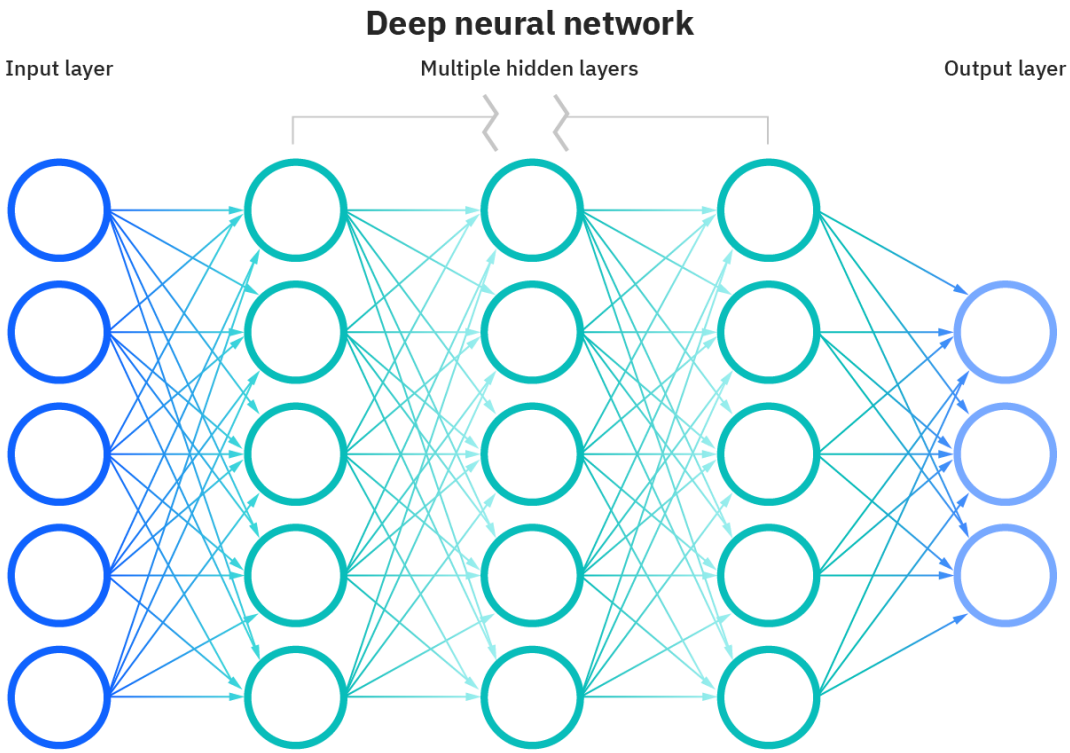

Figure 2: Deep Learning

Deep learning can be considered as a subset of machine learning. It is a field that is based on learning and improving on its own by examining computer algorithms. While machine learning uses simpler concepts, deep learning works with artificial neural networks, which are designed to imitate how humans think and learn. Until recently, neural networks were limited by computing power and thus were limited in complexity. However, advancements in Big Data analytics have permitted larger, sophisticated neural networks, allowing computers to observe, learn, and react to complex situations faster than humans. Deep learning has aided image classification, language translation, speech recognition. It can be used to solve any pattern recognition problem and without human intervention.

Neural networks are layers of nodes, much like the human brain is made up of neurons. Nodes within individual layers are connected to adjacent layers. The network is said to be deeper based on the number of layers it has. A single neuron in the human brain receives thousands of signals from other neurons. In an artificial neural network, signals

travel between nodes and assign corresponding weights. A heavier weighted node will exert more effect on the next layer of nodes. The final layer compiles the weighted inputs to produce an output. Deep learning systems require powerful hardware because they have a large amount of data being processed and involves several complex mathematical calculations. Even with such advanced hardware, however, training a neural network can take weeks.

Deep learning is finding its way into applications of all sizes. Anyone using Facebook cannot help but notice that the social platform commonly identifies and tags your friends when you upload new photos. Digital assistants like Siri, Cortana, Alexa, and Google Now use deep learning for natural language processing and speech recognition. Skype translates spoken conversations in real-time. Many email platforms have become adept at identifying spam messages before they even reach the inbox. PayPal has implemented deep learning to prevent fraudulent payments. Apps like CamFind allow users to take a picture of any object and, using mobile visual search technology, discover what the object is.

Deep learning is only in its infancy and, in the decades to come, will transform society. Self-driving cars are being tested worldwide; the complex layer of neural networks is being trained to determine objects to avoid, recognize traffic lights, and know when to adjust speed. Neural networks are becoming adept at forecasting everything from stock prices to the weather. Consider the value of digital assistants who can recommend when to sell shares or when to evacuate ahead of a hurricane. Deep learning applications will even save lives as they develop the ability to design evidence-based treatment plans for medical patients and help detect cancers early.

Most deep neural networks are feed-forward, meaning they flow in one direction only from input to output. However, you can also train your model through backpropagation; that is, move in opposite direction from output to input. Backpropagation allows us to calculate and attribute the error associated with each neuron, allowing us to adjust and fit the algorithm appropriately.

2.3.3. Artificial Neural Network

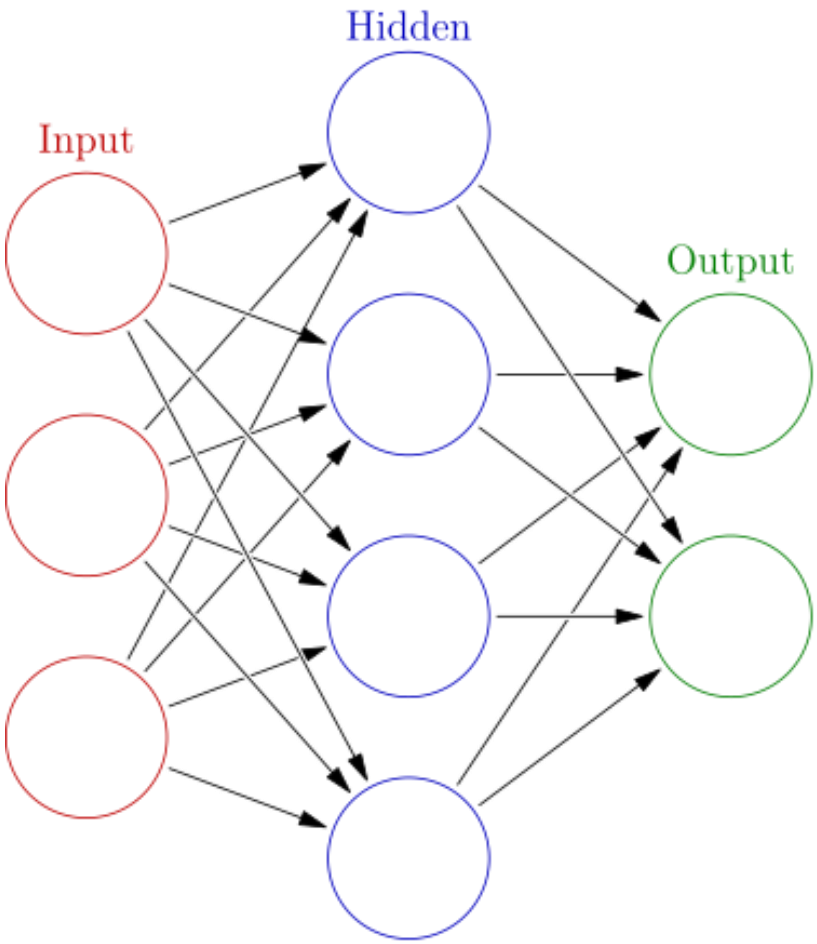

Figure 3: Artificial Neural Network

Artificial neural network (ANN) is a computational model that consists of several processing elements that receive inputs and deliver outputs based on their predefined activation function.

Artificial neural networks are a technology based on studies of the brain and nervous system. These networks emulate a biological neural network, but they use a reduced set of concepts from biological neural systems.

Specifically, ANN models simulate the electrical activity of the brain and nervous system. Processing elements (also known as either a neurode or perceptron) are connected to other processing elements. Typically, the neurodes are arranged in a layer or vector, with the output of one layer serving as the input to the next layer and other layers.

Input Layers

The input layer is the first layer of an ANN that receives the input information in the form of various texts, numbers, audio files, image pixels, etc.

Hidden Layers

In the middle of the ANN model are the hidden layers. There can be a single hidden layer, as in the case of a perceptron or multiple hidden layers. These hidden layers perform several types of mathematical computation on the input data and recognize the patterns that are part of.

Output Layer

In the output layer, I obtain the result that I obtain through rigorous computations performed by the middle layer.

2.3.4. Convolutional Neural Network

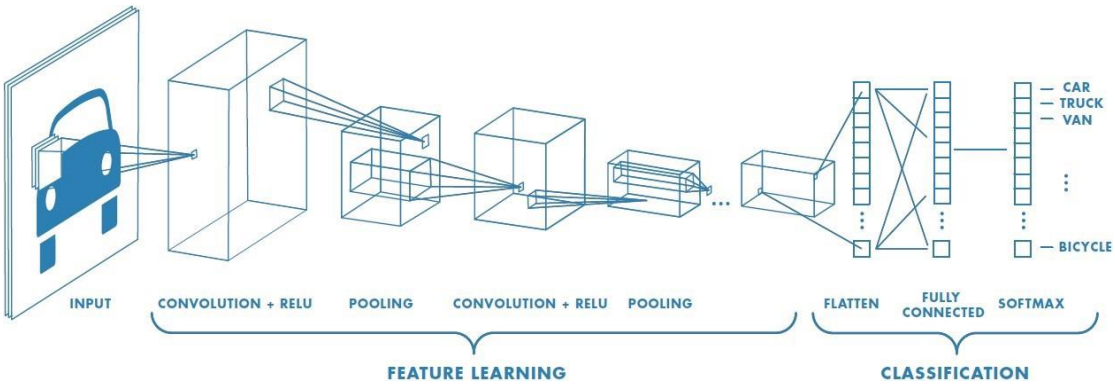

Figure 4: Convolutional Neural Network

In deep learning, a convolutional neural network (CNN, or ConvNet) is a class of artificial neural network (ANN), most commonly applied to analyse visual imagery. CNNs are also known as Shift Invariant or Space Invariant Artificial Neural Networks (SIANN), based on the shared-weight architecture of the convolution kernels or filters that slide along input features and provide translation-equivariant responses known as feature maps.

A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. The pre-

processing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive methods filters are hand-engineered, with enough training, ConvNets have the ability to learn these filters/characteristics.

The architecture of a ConvNet is analogous to that of the connectivity pattern of Neurons in the Human Brain and was inspired by the organization of the Visual Cortex. Individual neurons respond to stimuli only in a restricted region of the visual field known as the Receptive Field. A collection of such fields overlaps to cover the entire visual area.

2.3.5. Transfer Learning

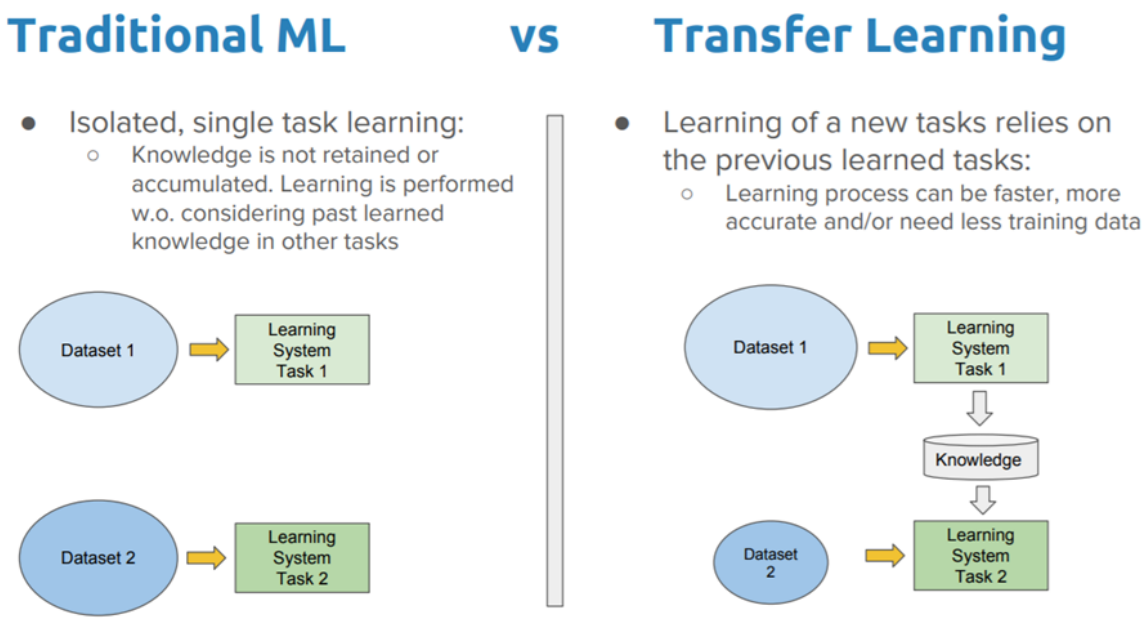

Figure 5: Traditional Learning vs Transfer Learning

Transfer learning is about leveraging feature representations from a pre-trained model, so you do not have to train a new model from scratch.

The pre-trained models are usually trained on massive datasets that are a standard benchmark in the computer vision frontier. The weights obtained from the models can be reused in other computer vision tasks.

These models can be used directly in making predictions on new tasks or integrated into the process of training a new model. Including the pre-trained models in a new model leads to lower training time and lower generalization error.

The first thing to remember here is that transfer learning, is not a new concept which is extremely specific to deep learning. There is a stark difference between the traditional approach of building and training machine learning models and using a methodology following transfer learning principles.

Traditional learning is isolated and occurs purely based on specific tasks, datasets and training separate isolated models on them. No knowledge is retained which can be transferred from one model to another. In transfer learning, you can leverage knowledge (features, weights etc) from previously trained models for training newer models and even tackle problems like having less data for the newer task

2.4. Data Science & Analytics Tools

Figure 6: Python

Figure 7: MITK Workbench

The analytical tool will be Python. Python provides great libraries to deal with data science applications. Python is an incredibly old and extremely popular programming language for data science-related projects. It has an exceptionally large library and community support for machine learning applications.

It has vast number of pre-defined models for machine learning. For deep learning, Python is considered to be the best tool for model building and analyzing the data. Convolutional Neural Network (CNN), Artificial Neural Network (ANN) and Transfer learning can be done on Python easily.

As this is a research project and is a deep learning project, it is advised not to use any data visualization tools like PowerBI and Tableau. And it is also overly complex to be used in the deep learning projects as it does not serve any purpose and value.

MITK Workbench, which is open-source application is used for visualizing the DICOM files and process the data as required. It gives us so many views and which one I need in the project can be seen easily and extracted accordingly.

3. CHAPTER 3

RESEARCH METHODOLOGY

3.1. Activities Plan and Gantt Chart

The Gantt chart with the activity plan for this project is determined according to the data science project lifecycle. The project started on first week of April 2021 and end on last week of July 2021. The following Figure 8 (Gantt Chart) shows the plan of the project progression of practicum:

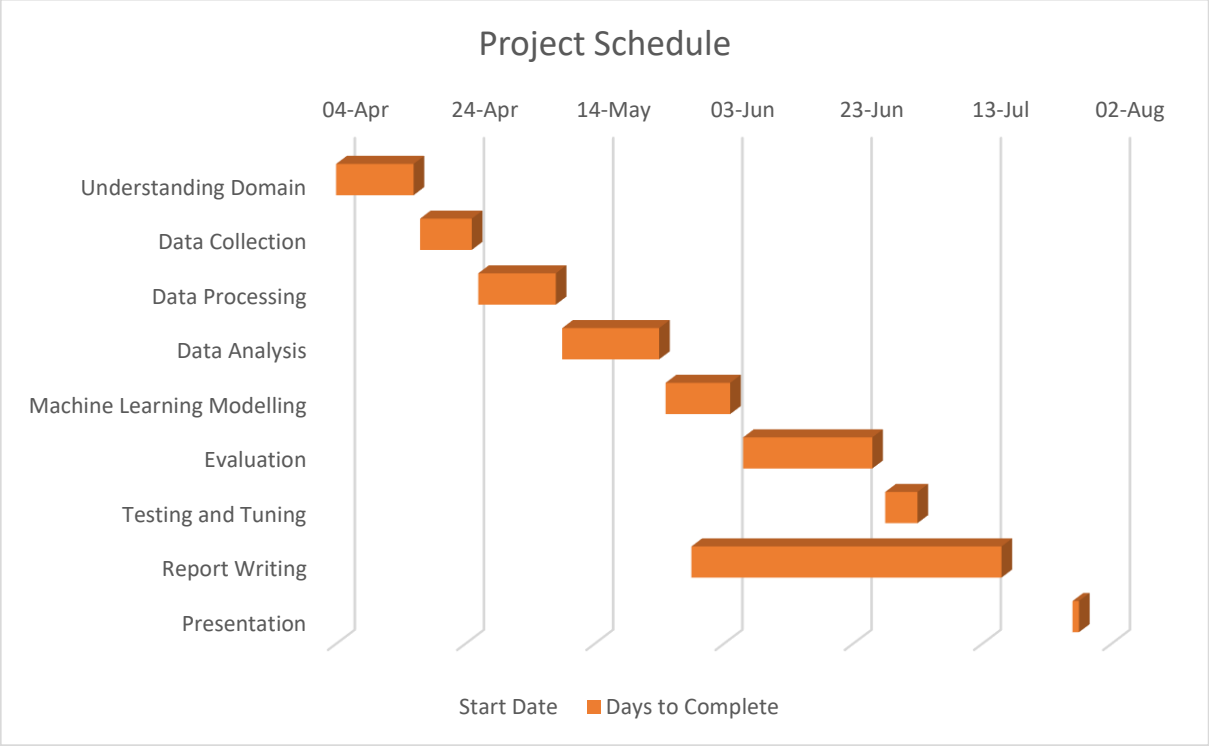

Figure 8: Project Gantt Chart

This project is completed within the duration provided. Understanding the domain is very crucial when working on a health sector project. Basic knowledge of the domain is preferable to be able to understand the idea. Data collection is a time taking process as it needed to be processed by the radiologist. Firstly, having a little idea about deep learning was not helping so I had to understand the domain. Read many articles, watched many tutorials in order to keep the pace of the work smooth and nice outcome. The major part was to change the format of the data in order to pass it to the model, discussed in the below section. Then the data analysis was done which is also important part of the process. After analysing, I decided to split the data into 70:30 meaning 70%

as training and 30% as testing data. The most difficult part was to apply machine learning, convolutional neural networks on the dataset. After that I tested and tuned data which is a time-consuming process in the deep learning approaches as the computation power required is high and having a medium specification machine was not helping. Managed to get higher accuracy and evaluate the USM dataset.

3.2. Data Science Project Lifecycle

The proposed framework shown in Figure 9 and the deep learning lifecycle is also shown in the Figure 10 below and is created and modified based on the concept of four nested levels of visualization design in Munzner book and CRISP-DM which are shown in Figure 11 and Figure 12 respectively.

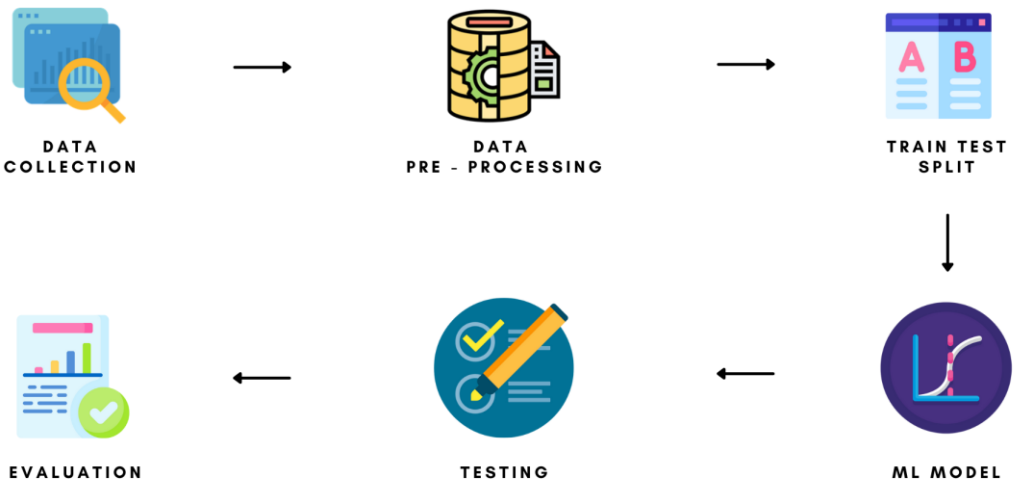

Figure 9: Framework of Proposed Solution

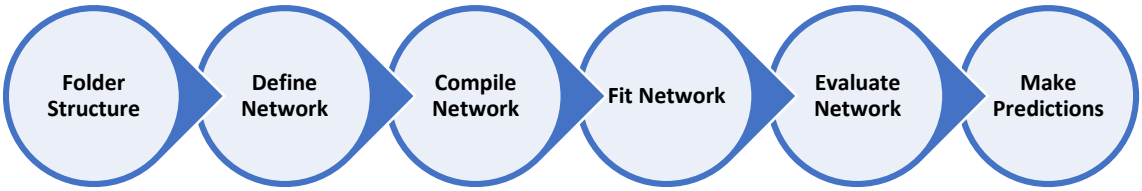

Figure 10: Deep Learning Lifecycle

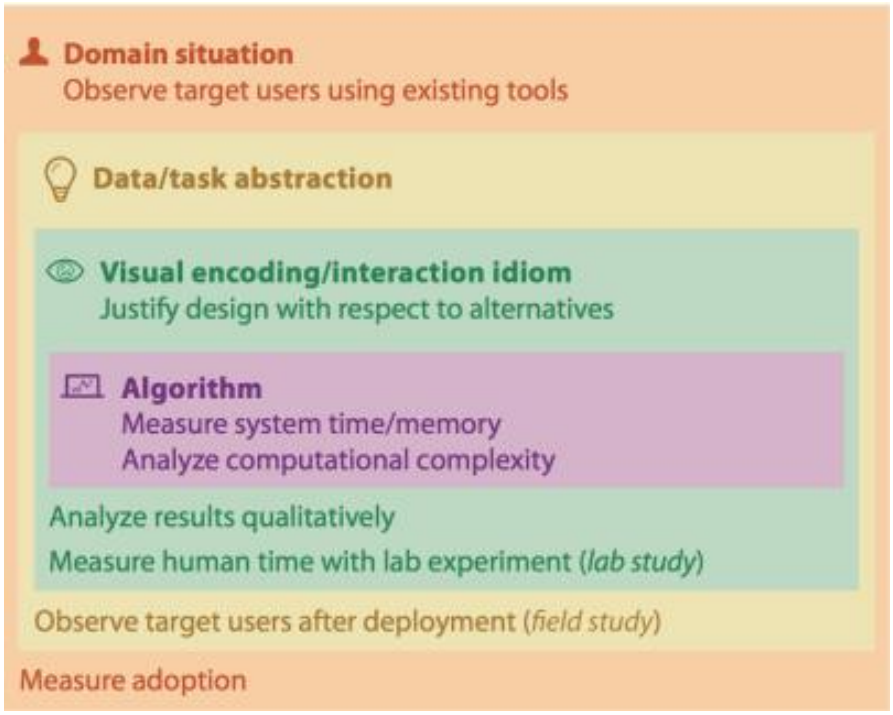

Figure 11: Framework of Four-nested Visualization

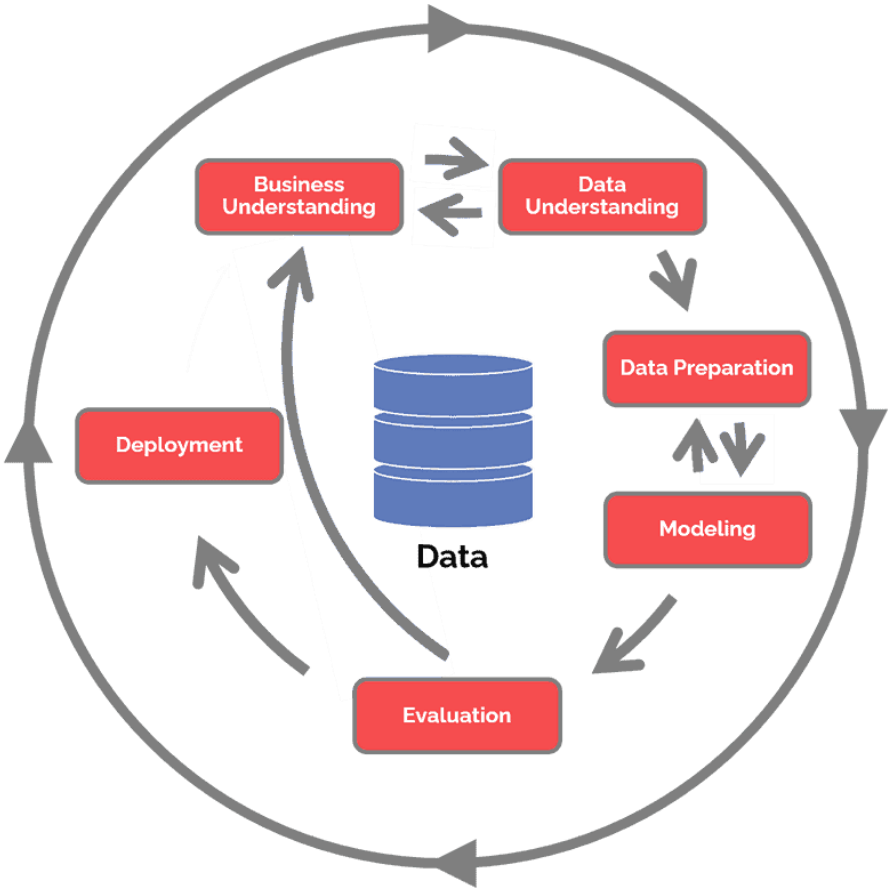

Figure 12: Framework of CRISP-DM

3.3. Domain Situation

This step involves contracting with my mentor, Dr Johari Yap Abdullah to understand on the background of the School of Dental Science (Health Campus), USM and the issues faced by the doctors and radiologist.

Doctors use many tests to find, or analyse, a brain tumour and learn the type of brain tumour. They also do tests to find out if it has spread to another part of the body from where it started. Doctors may also do tests to learn which treatments could work. For most types of tumours, taking a sample of the possible tumour is the only sure way for the doctor to know if an area of the body has a tumour.

This may be done in a procedure called a biopsy or by removing part or all of the tumour with surgery. In a biopsy, the doctor takes a small sample of tissue for testing in a laboratory. If this is not possible, the doctor may suggest other tests that will help make a diagnosis.

This project aims to build a machine learning model (deep learning) for USM Health Campus. The target users of this system are the people from health campus i.e., doctors and radiologists at USM Health Campus specifically my mentor, Dr Johari Yap Abdullah to help them to assess and examine the MRI images related to the expected brain tumour rapidly. The focus of creating this model is maintaining finding the higher accuracy with the public dataset and higher validation accuracy on testing dataset.

The overview of the machine learning model is shown below in Figure 13. The main components of the proposed solution are public dataset, the deep learning-based model and the USM data for testing.

Figure 13: Overview of Proposed Solution

3.4. Data Collection

Data used in this project are provided by my mentor Dr Johari Yap Abdullah who is a Senior Lecturer teaching Oral and Maxillofacial Radiology at the School of Dental Sciences, Health Campus, Universiti Sains Malaysia, Kubang Kerian, Kelantan, Malaysia as well as supervising Master and PhD students. The data is collected from the Radiology department of the USM Health Campus in the raw format. The data needed to be further processed with data pre-processing. After discussing with the Midterm panellist, I both (me and my mentor) agreed to use public dataset for the project as the dataset originally provided by the mentor was very less making it nonsensible project.

I used **Kaggle** to find the relevant data for our project. After researching and exploring, I found the source (HAMADA, 2022) to get the dataset. After importing the public dataset, I mixed the dataset with the original dataset in order to apply it to the machine learning model or deep learning model. The total amount of images I finally managed to get for the project including original data is 1360 images, almost 10 times the original dataset. The data on Kaggle is publicly available for use in the in the projects. The data will be expanding in future and web application will be required to further process the data on the server side.

The original dataset was in two kinds of folder namely normal and abnormal meaning the normal ones are the ones with no brain tumour but the abnormal ones containing the brain tumour images.

3.5. Data Pre-Processing

The raw data is in the DICOM format (dcm extension). The data provided by mentor Dr Johari Yap Abdullah are MRI data which can be viewed by the open-source MITK Software. The neural network algorithm does not support the dcm format of the images. The data needs to be changed into correct format as jpg, jpeg, .png, or tiff for feeding into the neural network algorithms.

Convert the data into jpg format, firstly, the pixel array is extracted from the DICOM files using Pydicom library and then input the changed into NumPy arrays to be further scaled. After scaling the total images, I got 147 images which is the original dataset

from the dcm format. For conversion, I have used libraries like Matplotlib, NumPy, OS, PIL, UUID and Pydicom (https://pydicom.github.io/).

Pydicom is a pure Python package for working with DICOM files. It lets you read, modify, and write DICOM data in an easy "pythonic" way. As a pure Python package, Pydicom can run anywhere Python runs without any other requirements. It is advised to use NumPy when working with pixel data as I have already mentioned above usage of the package.

The Figure 14 below shows the code required to convert the image from. dcm to .jpg is quite simple and pythonic way. I have defined a function named load_images and I needed to pass the source folder and destination folder as the arguments.

```
import matplotlib.image as mpimg
import pydicom
import numpy as np
from PIL import Image
import os
import uuid
def load_images(folder, DESTINATION_PATH):
    for filename in os.listdir(folder):
        ds = pydicom.dcmread(os.path.join(folder, filename))
        x = filename.split(".")
        x = x[3]
        name = uuid.uuid4().hex[:6].upper()+".jpg"
        print(name)
        new_image = ds.pixel_array.astype(float)

        scaled_image = (np.maximum(new_image, 0) / new_image.max()) * 255.0

        scaled_image = np.uint8(scaled_image)
        final_image = Image.fromarray(scaled_image)

        final_filepath = os.path.join(DESTINATION_PATH, name)

        final_image.save(final_filepath)
```

Figure 14: DICOM to JPG

Using the public dataset (HAMADA, 2022), I managed to get 3000 images of normal and abnormal MRI images in the jpg format, and it did not require any pre-processing for conversion to any other format.

After pre-processing, the dataset got reduced to 2884 because of RGB channel application on the source dataset. The shape of dataset is (2884, 128, 128, 3) which means a total of 2884 images with size of 128 × 128 and 3 (RGB colour) channels. The

dataset than converted into array using NumPy library with the maximum value as 255 and the minimum value as 0. Then the data is reduced between the 1 and 0 value by dividing the data with 255. Now the maximum value as 1.0 and the minimum value as 0.0.

We, then split the dataset using the scikit-learn library module called train_test_split.

```
x_train,x_test,y_train,y_test = train_test_split(data, labels, test_size=0.3, shuffle=True, random_state=7)
```

Figure 15: Train Test Split

The dataset is split up into training sets and test sets with 70% going to training and 30% going to the testing. The data is split into 4 variables namely x_train, x_test, y_train, y_test and the shape of the dataset are (2018, 128, 128, 3), (2018, 1), (866, 128, 128, 3), and (866, 1) respectively (see Figure 15).

3.6. Proposed Solution and Justification

The model needed more images to be trained to get more accuracy. While applying the deep learning methods, the main concern was on to find the optimal model accuracy and reduced loss. Then again, the computation power needed should be taken into consideration as deep learning models needs high performance hardware to work faster and efficiently. As it is a binary classification problem, populating with classification report is also important as it is performance evaluation metrics of a classification-based machine learning model. It displays your model's precision, recall, F1 score and support. It provides a better understanding of the overall performance of our trained model. Understand the classification report of a machine learning model, we need to know all of the metrics displayed in the report.

Deep learning model tries to generalize the data using an algorithm and tries to make predictions on the unseen data. We need an algorithm that maps the examples of inputs to that of the outputs and an optimization algorithm. An optimization algorithm finds the value of the parameters (weights) that minimize the error when mapping inputs to outputs. These optimization algorithms or optimizers widely affect the accuracy of the deep learning model. They as well as affect the speed training of the model. While training the deep learning model, we need to modify each epoch's weights and minimize the loss function. An optimizer is a function or an algorithm that modifies the attributes

of the neural network, such as weights and learning rate. Thus, it helps in reducing the overall loss and improve the accuracy.

I am using Adam optimizer because the results of the Adam optimizer are better than every other optimization algorithm, have faster computation time, and require fewer parameters for tuning. Adam is recommended as the default optimizer for most of the applications. Choosing the Adam optimizer for my application might gave me the best results.

While compiling the model I also used cross entropy loss function. It is an optimization function used in training classification models that classify data by predicting the probability that the data will belong to one class or another.

The number of epochs I used while fitting the model is 200 which is considerable number of training epochs and needs more computation power. The kernel died so many times while training the model because of high epochs and it is also necessary to have an ample number of epochs. Because of low computational power and kernel deaths, I had to use early stopping in order to prevent overfitting. This method allowed me to specify an arbitrary considerable number of training epochs and stop training once the model performance stops improving on a holdout validation dataset.

Finally, the structure of the folder is shown below in the Figure 16.

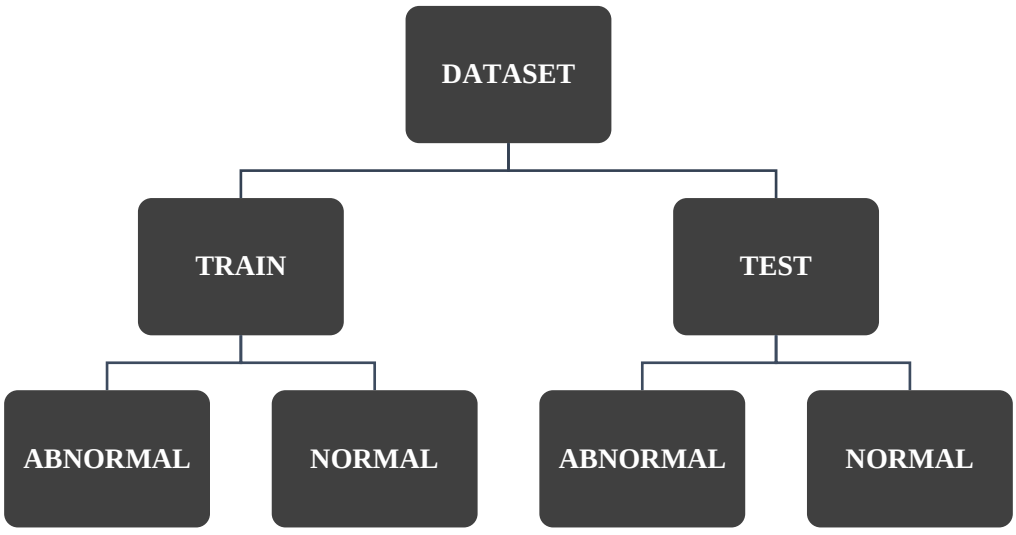

Figure 16: Folder Structure

4. CHAPTER 4

RESULTS AND DISCUSSION

4.1. Comparison of Accuracy and Loss

4.1.1. Baseline

The models used in this project are Sequential and VGG16. The Sequential model is a linear stack of layers. The common architecture of ConvNets is a sequential architecture. However, some architectures are not linear stacks. VGG-16 is a convolutional neural network that is 16 layers deep. You can load a pretrained version of the network trained on more than a million images from the ImageNet database. The pretrained network can classify images into thousands of object categories.

The model has been trained 3 times using Sequential and Transfer Learning, once with normal data and then with augmented data by flipping the images horizontally.

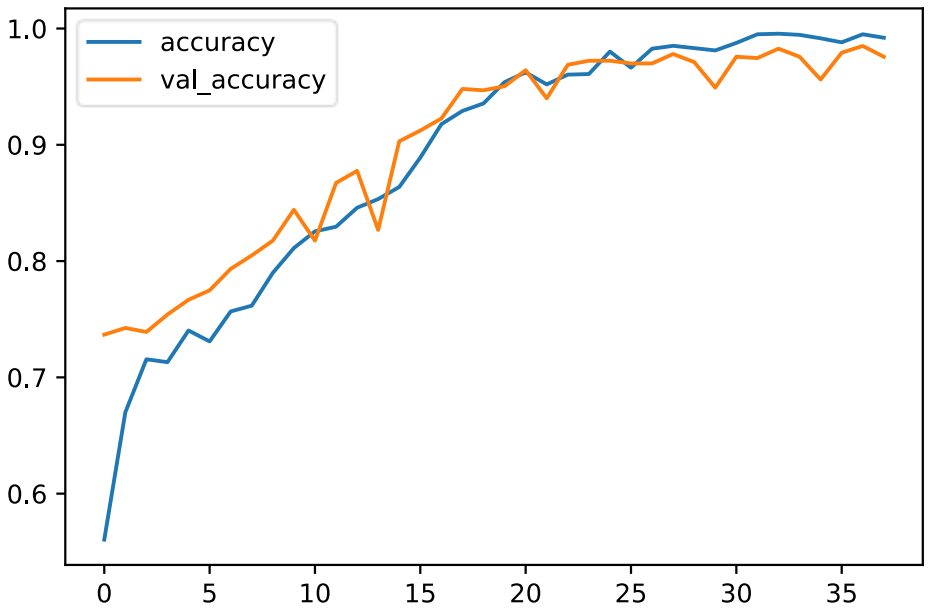

Figure 17: Baseline – Accuracy vs Validation Accuracy

The graph above in Figure 17 shows the accuracy of the baseline model. The baseline model Sequential gave the accuracy of 99% and validation accuracy of 97.6%.

After applying data augmentation, the accuracy increased in both, with the accuracy of 100% and validation accuracy of 98.50%. Lastly, when transfer learning was applied the mode gave the accuracy of 100% and validation accuracy of 98.96%.

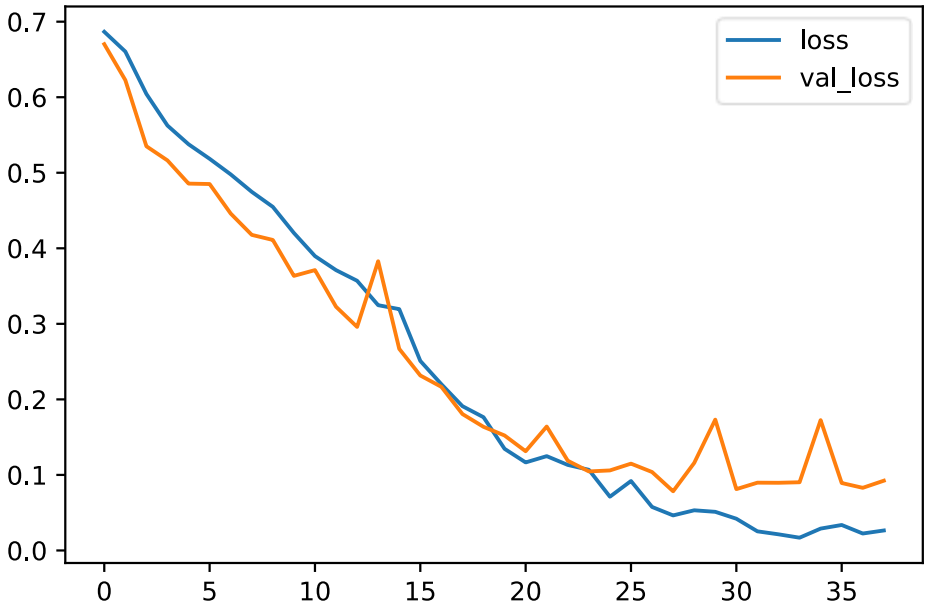

Figure 18: Baseline – Loss vs Validation Loss

The baseline model also showed nice scores in the form of Loss and Validation Loss as shown in the Figure 18. The loss is at 0.0265 and validation loss is at 0.0924 which quite low. But the model showed some hindrance at the last observations of model.

These scores are quite good for a baseline model as no hyperparameter tuning was done. With default setting the model showed high accuracy scores and low loss scores which are quite exciting.

4.1.2. Data Augmentation

After the baseline model, I applied a technique called data augmentation. This method generates more data. After adding a layer that flips our images horizontally creating more data for our model to train on.

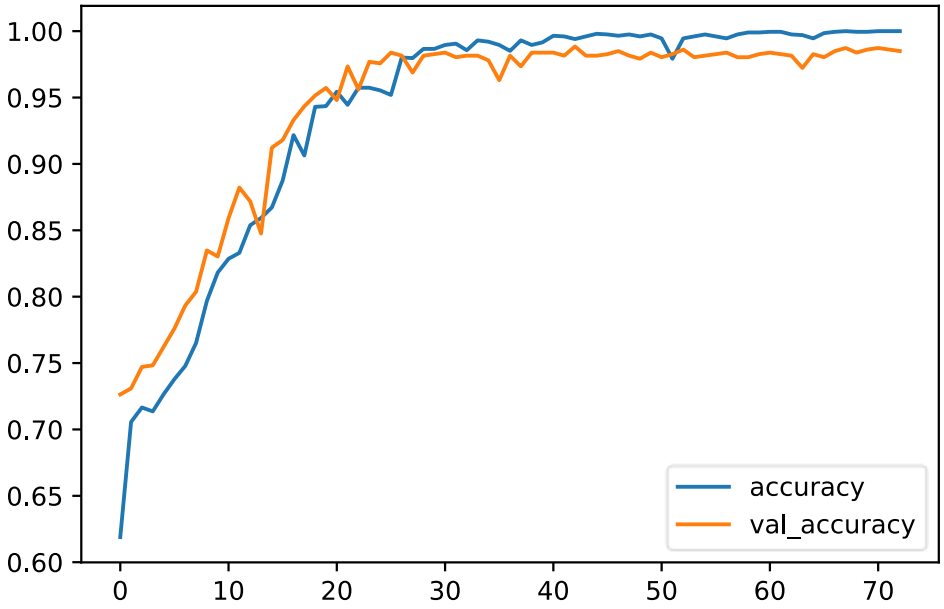

Figure 19: Augmented - Accuracy vs Validation Accuracy

After applying data augmentation, the accuracy increased in both. The model gave the accuracy of 100% and validation accuracy of 98.50% as shown in the Figure 19.

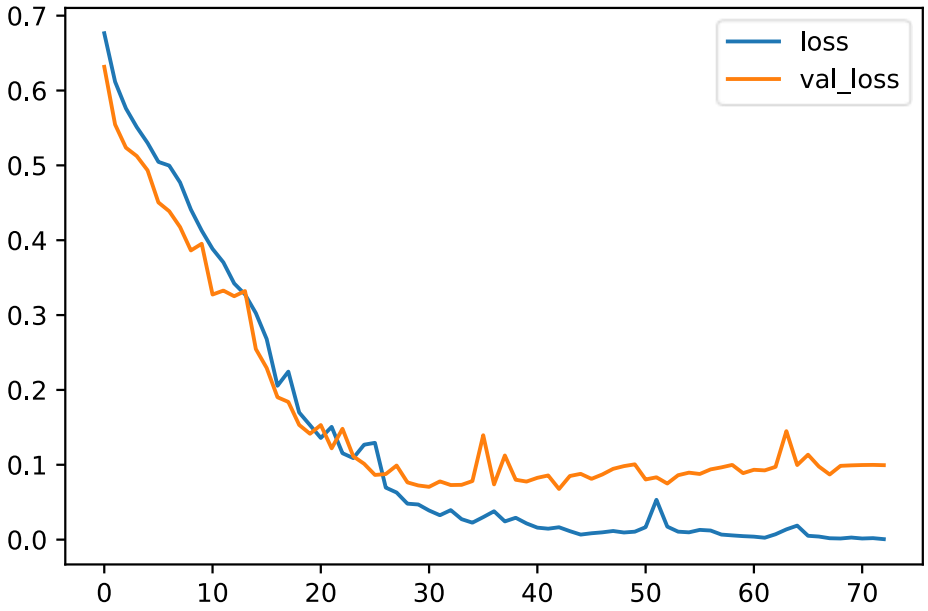

Figure 20: Augmented - Loss vs Validation Loss

The model after data augmentation also showed nice score in the form of Loss and increased by fraction in Validation Loss as shown in the Figure 20. The loss is at 0.00064 and validation loss is at 0.0995 which quite low. But the model showed some hindrance at the last observations of model.

4.1.3. Transfer Learning

In the transfer learning, I added a pretrained model VGG16 (Visual Geometry Group). I also used pretrained weights in VGG16 model and applied data augmentation by adding a layer to flip the images left to right.

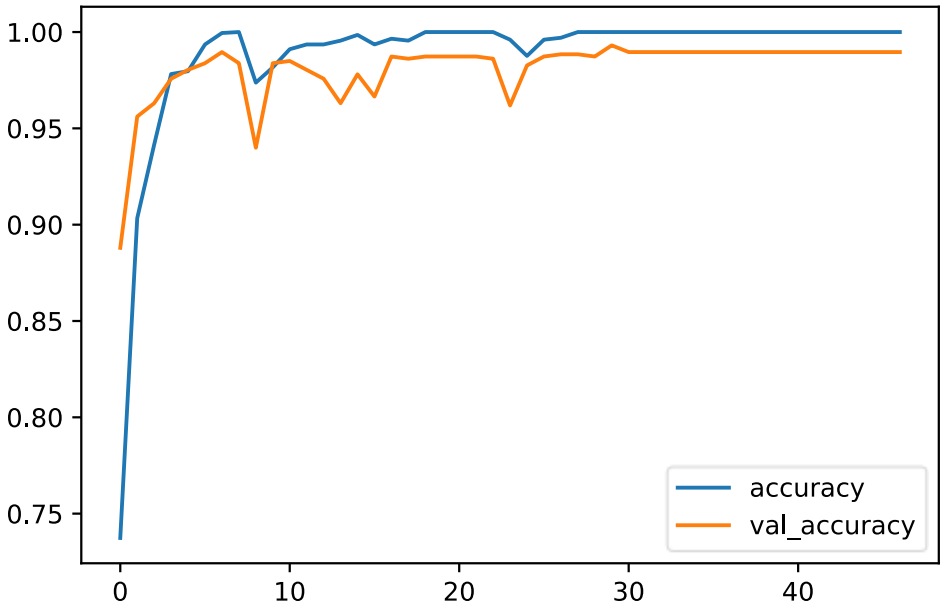

Figure 21: Transfer Learning - Accuracy vs Validation Accuracy

After applying transfer learning using a pretrained VGG16 model, the accuracy increased in validation set. The model gave the accuracy of 100% and validation accuracy of 99% as shown in the Figure 21.

The accuracy increased in validation by 1% giving my previous model with data augmentation a quite nice review.

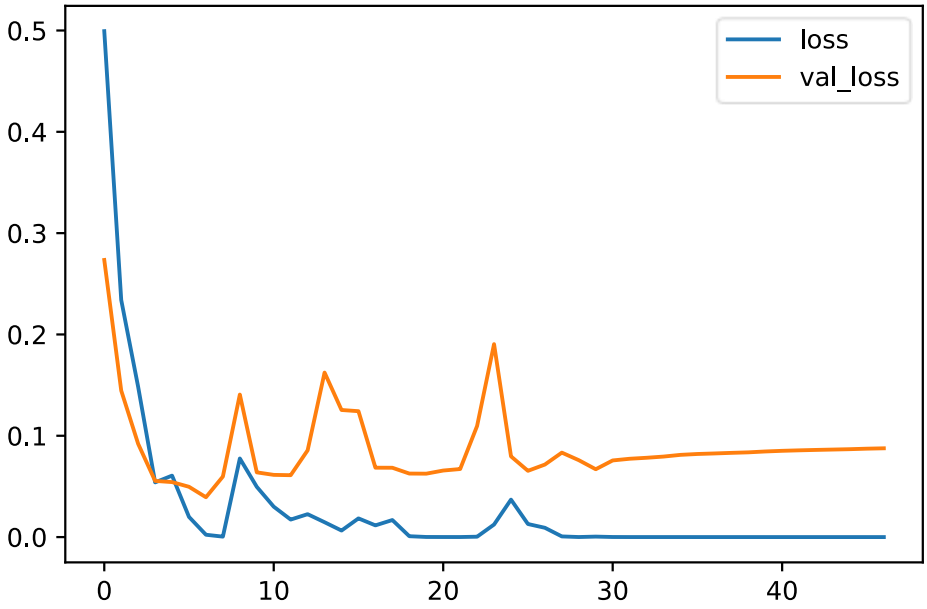

Figure 22: Transfer Learning - Loss vs Validation Loss

Transfer learning method also showed nice scores in the form of Loss and Validation Loss as shown in the Figure 22. The loss is at 0.0000092 and validation loss is at 0.0876 which quite low from the previous models.

All the models showed ample performance, which I did not expect. Having higher accuracy models in both situations is genuinely nice. The models are working nice and having higher scores as compared to the other traditional models which has been done in the past and mentioned in the related works sections.

4.2. Challenges and Solutions

First challenge was to understand what deep learning is and how it works and what are pre-requisites for it. What should I know about before moving into this domain? Having said that another challenge was to find a nice dataset as the USM dataset has to be used in the testing and is of course very less in amount. Last but not the least, hardware requirements for deep learning are quite high and expensive.

The solutions are quite simple as I studied about deep learning and found that it is a subset of machine learning and needs some more computation power than to what I was

using from the starting of the course. Found the public dataset on Kaggle with little bit of research and keeping in mind that my machine cannot handle a larger dataset.

Finally, I believe that I could do it and support from my mentor and supervisor is extremely nice, I managed to apply deep learning methodologies on my machine even it took much longer to run.

4.3. Application of Class learning

After getting into USM, this machine learning course and I found it remarkably interesting, but yet so tough but enjoyed a lot. The things I learned in the class with every hour and day of machine learning course and practice. I got to know the basics which helped in learning and applying my basic knowledge in deep learning.

5. CHAPTER 5

CONCLUSION AND LESSON LEARNED

5.1. Conclusion

This project is able to answer the research questions and achieve the project objectives within the duration. The objectives have been achieved and problems have been solved. I have found that the models I made are quite nice performing model. The models have nice scores as compared to the traditional models been developed in the past and in the related works.

I conclude that deep learning is indeed an especially important field and is going to overtake so many industries. But it needs high computation which comes at a price.

The research questions can be answer below as follows:

- How these files (DICOM) can be converted to fit into machine learning model.

  The DICOM files turned out to be very interesting as it contains humongous data. Can be converted to jpg and png easily with the help of Pydicom library. A small and basic python knowledge is required and if working with pixel data, I need to import NumPy too.

- Predicting the tumour rapidly to be used by the surgeon for patients.

  Predicting the tumour rapidly is achievable with the help of deep learning techniques. After finding the best model I applied it on to test data which contains 866 images of tumorous and non-tumorous data. The model is quite fast in predicting as it took 3 seconds to predict the labels for each of the images.

- How the prediction of glioma can help the surgeon in robust diagnosis.

  The time taken by the model is very low as it is predicting 866 images in just 3 seconds which is quite fast and if the machine has ample performing hardware, it will be working faster than that. For now, the model can predict 288 images in just a second. This will help in diagnosis as the data that has been used to train the model contains images of tumorous and non-tumorous at so many levels making it predictable for early-stage tumours.

5.2. Lesson Learned

The soft skill learnt throughout this practicum is communication skill. In this project, contracting with mentor throughout the project is important to understand the requirements of project and convey information to the mentor as well. At the beginning, the difficulty faced is due to lack of understanding on the deep learning but overcome by studying and practicing.

After communicating with mentor and supervisor, this barrier is overwhelmed through the detailed explanation from them. The ability to communicate with supervisor also helped in working efficiently. They guided me during virtual meeting on Webex meetings and over WhatsApp calls.

5.3. Future Scope and Opportunities

Due to the duration for this practicum is only four months, there are some opportunities that yet to be explored. The model can be improved further by adding more data for training and applying more different models and transfer learning techniques.

In future, I can think of doing PhD or work in the organisations where deep learning is used as it especially important and game changing domain.

The future scope of the project can be improving the accuracy and deploying it on the world wide web with robust and secure applications so as to maintain secrecy with patients' data.

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APPENDIX

6.1. Python Code

In [ ]:

```
import matplotlib.image as mpimg
import pydicom
import numpy as np
from PIL import Image
import os
import uuid
def load_images(folder, DESTINATION_PATH):
    for filename in os.listdir(folder):
        ds = pydicom.dcmread(os.path.join(folder, filename))
        x = filename.split(".")
        x = x[3]
        name = uuid.uuid4().hex[:6].upper()+".jpg"
        print(name)
        new_image = ds.pixel_array.astype(float)

        scaled_image = (np.maximum(new_image, 0) / new_image.max()) * 255.0

        scaled_image = np.uint8(scaled_image)
        final_image = Image.fromarray(scaled_image)

        final_filepath = os.path.join(DESTINATION_PATH, name)

        final_image.save(final_filepath)
```

In [ ]:

```
for i in range(1,4):
    folder = "Dataset/Abnormal/Abnormal "+str(i)+"/Abnormal "+str(i)+" T2W"
    DESTINATION_PATH = 'NewDataset/Abnormal'
    load_images(folder, DESTINATION_PATH)
```

In [ ]:

```
for i in range(1,4):
    folder = "Dataset/Normal/Normal "+str(i)+"/Normal "+str(i)+" T2W"
    load_images(folder, DESTINATION_PATH = 'NewDataset/Normal')
```

Figure 23: Code: Convert DICOM – JPG

1. Importing the libaries

```
#importing libaries
import numpy as np
import pandas as pd
import random as rd
import os

import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

from PIL import Image

from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score, confusion_matrix, \
                            classification_report, accuracy_score, precision_score, f1_score, recall_score

import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
from tensorflow.keras.layers.experimental import preprocessing
from keras.metrics import accuracy
from keras.applications.vgg16 import VGG16
from tensorflow.keras.applications import VGG19

#setting seed for reproducability
from numpy.random import seed
seed(25)
tf.random.set_seed(50)

import warnings
warnings.filterwarnings('ignore')
```

Figure 24: Code: Deep Learning

2. Importing the images

```
data = [] #creating a list for images
paths = [] #creating a list for paths
labels = [] #creating a list to put our 0 or 1 labels

#staring with the images that have tumors
for r, d, f in os.walk(r'Dataset/Abnormal/'):
    for file in f:
        if '.jpg' in file:
            paths.append(os.path.join(r, file))

for path in paths:
    img = Image.open(path)
    img = img.resize((128,128))
    img = np.array(img)
    if(img.shape == (128,128,3)):
        data.append(np.array(img))
        labels.append(1)

#now working with the images with no tumors
paths = []
for r, d, f in os.walk(r"Dataset/Normal/"):
    for file in f:
        if '.jpg' in file:
            paths.append(os.path.join(r, file))

for path in paths:
    img = Image.open(path)
    img = img.resize((128,128))
    img = np.array(img)
    if(img.shape == (128,128,3)):
        data.append(np.array(img))
        labels.append(0)
data = np.array(data)
data.shape

labels = np.array(labels)
labels = labels.reshape(2884,1)

print('Data shape is:', data.shape)
print('Labels shape is:', labels.shape)
```

Figure 25: Code: Deep Learning

3. Processing the images

3.1 Changing pixel values

Each pixel has a value between 255 and 0. We will reduce this down to 1 and 0 in order to help the neural network converge quicker.

```
#getting the max of the array
print(np.max(data))
#getting the min of the array
print(np.min(data))

#reducing the data to between 1 and 0
data = data / 255.00
#getting the max of the array
print(np.max(data))
#getting the min of the array
print(np.min(data))
```

Figure 26: Code: Deep Learning

3.2 Visualizing the images

```
for i in range(5):
    fig = plt.figure(figsize=(40,40))
    plt.subplot(5,5,i+1)
    image = plt.imshow(data[i])
    plt.show(image)
```

Figure 27: Code: Deep Learning

3.2 Graph Save Function

```
def savePlot(name):
    name = name+'.svg'
    plt.savefig(name, format='svg', dpi=1200)
```

Figure 28: Code: Deep Learning

4 Model

4.1 Creating training and test sets

Before we create our model we will split up the data into training sets and test sets with 70% going to training and 30% going to testing.

```
x_train,x_test,y_train,y_test = train_test_split(data, labels, test_size=0.3, shuffle=True, random_state=7)

print("shape of our training data:",x_train.shape)
print("shape of our training labels:",y_train.shape)
print("shape of our test data:",x_test.shape)
print("shape of our test labels:",y_test.shape)
```

Figure 29: Code: Deep Learning

4.2 Creating our baseline model

```
model = keras.Sequential([

    layers.Conv2D(filters=32, kernel_size=(5,5), activation="relu", padding='same', input_shape=[128, 128, 3]),
    layers.MaxPool2D(),

    layers.Conv2D(filters=64, kernel_size=(3,3), activation="relu", padding='same'),
    layers.MaxPool2D(),

    layers.Conv2D(filters=128, kernel_size=(3,3), activation="relu", padding='same'),
    layers.MaxPool2D(),

    layers.Conv2D(filters=128, kernel_size=(3,3), activation="relu", padding='same'),
    layers.MaxPool2D(),

    layers.Flatten(),
    layers.Dropout(.30),
    layers.Dense(units=256, activation="relu"),
    layers.Dense(units=1, activation="sigmoid"),
])

model.summary()
model.name

model.compile(
    optimizer=tf.keras.optimizers.Adam(epsilon=0.01),
    loss='binary_crossentropy',
    metrics=['accuracy']
)

#including early stopping to prevent overfitting
early_stopping = keras.callbacks.EarlyStopping(
    patience=10,
    min_delta=0.001,
    restore_best_weights=True,
)

print("Fit model on training data")
history = model.fit(
    x = x_train,
    y = y_train,
    validation_data= (x_test,y_test),
    batch_size = 64,
    epochs=200,
    callbacks=[early_stopping],
    verbose=(2),
)
```

Figure 30: Code: Deep Learning

```
history_frame = pd.DataFrame(history.history)
history_frame.loc[:, ['loss','val_loss']].plot()
savePlot('baseline_loss_valloss')
history_frame.loc[:, ['accuracy','val_accuracy']].plot();
savePlot('baseline_acc_valacc')
```

Figure 31: Code: Deep Learning

```
pred = model.predict(x_test)

for i in range(len(pred)):
    if pred[i] > 0.5:
        pred[i] = 1
    else:
        pred[i] = 0

pred = pred.astype(int)
```

Figure 32: Code: Deep Learning

```
#creating a classification report
print(classification_report(y_test, pred))
```

Figure 33: Code: Deep Learning

4.3 Adding data agumentation

```
model = keras.Sequential([

    preprocessing.RandomFlip('horizontal'), # flip left-to-right

    layers.Conv2D(filters=32, kernel_size=(5,5), activation="relu", padding='same', input_shape=[128, 128, 3]),
    layers.MaxPool2D(),

    layers.Conv2D(filters=64, kernel_size=(3,3), activation="relu", padding='same'),
    layers.MaxPool2D(),

    layers.Conv2D(filters=128, kernel_size=(3,3), activation="relu", padding='same'),
    layers.MaxPool2D(),

    layers.Conv2D(filters=128, kernel_size=(3,3), activation="relu", padding='same'),
    layers.MaxPool2D(),

    layers.Flatten(),
    layers.Dropout(.25),
    layers.Dense(units=256, activation="relu"),
    layers.Dense(units=1, activation="sigmoid"),
])

model.compile(
    optimizer=tf.keras.optimizers.Adam(epsilon=0.01),
    loss='binary_crossentropy',
    metrics=['accuracy']
)

#including early stopping to revent overfitting
early_stopping = keras.callbacks.EarlyStopping(
    patience=30,
    min_delta=0.001,
    restore_best_weights=True,
)

print("Fit model on training data")
history = model.fit(
    x = x_train,
    y = y_train,
    validation_data= (x_test,y_test),
    batch_size = 64,
    epochs=200,
    callbacks=[early_stopping],
    verbose=(2),
)
```

Figure 34: Code: Deep Learning

```
history_frame = pd.DataFrame(history.history)
history_frame.loc[:, ['loss','val_loss']].plot()
savePlot('augmented_loss_valloss')
history_frame.loc[:, ['accuracy','val_accuracy']].plot();
savePlot('augmented_acc_valacc')
```

Figure 35: Code: Deep Learning

```
pred = model.predict(x_test)

for i in range(len(pred)):
    if pred[i] > 0.5:
        pred[i] = 1
    else:
        pred[i] = 0

pred = pred.astype(int)
```

Figure 36: Code: Deep Learning

```
#creating a classification report
print(classification_report(y_test, pred))
```

Figure 37: Code: Deep Learning

4.4 Adding a pretrained model

```
# load base model
vgg16_weight_path = 'vgg16_weights_tf_dim_ordering_tf_kernels_notop.h5'
base_model = VGG16(
    weights=vgg16_weight_path,
    include_top=False,
    input_shape=(128,128,3)
)
```

Figure 38: Code: Deep Learning

```
model = keras.Sequential([

    preprocessing.RandomFlip('horizontal'), # flip left-to-right

    base_model, #vgg16

    layers.Flatten(),
    layers.Dropout(.25),
    layers.Dense(units=256, activation="relu"),
    layers.Dense(units=1, activation="sigmoid"),
])

model.compile(
    optimizer=tf.keras.optimizers.Adam(epsilon=0.01),
    loss='binary_crossentropy',
    metrics=['accuracy']
)

#including early stopping to prevent overfitting
early_stopping = keras.callbacks.EarlyStopping(
    patience=40,
    min_delta=0.001,
    restore_best_weights=True,
)

print("Fit model on training data")
history = model.fit(
    x = x_train,
    y = y_train,
    validation_data= (x_test,y_test),
    batch_size = 64,
    epochs=200,
    callbacks=[early_stopping],
    verbose=(2),
)
```

Figure 39: Code: Deep Learning

```
history_frame = pd.DataFrame(history.history)
history_frame.loc[:, ['loss','val_loss']].plot()
savePlot('vgg16_loss_valloss')
history_frame.loc[:, ['accuracy','val_accuracy']].plot();
savePlot('vgg16_acc_valacc')
```

Figure 40: Code: Deep Learning

```
pred = model.predict(x_test)

for i in range(len(pred)):
    if pred[i] > 0.5:
        pred[i] = 1
    else:
        pred[i] = 0

pred = pred.astype(int)
```

Figure 41: Code: Deep Learning

```
#creating a classification report
print(classification_report(y_test, pred))
```

Figure 42: Code: Deep Learning

```
model.save("model_VGG16.h5", save_format='h5')
```

Figure 43: Code: Deep Learning

6.2. Logbook

CS-PracTIS::USM				
#	**Date/Day**	**Time/Hours Spent**	**Notes**	**Review**
1	07-Apr-2022, Thursday	14:00 - 14:30 (00:30)	First meeting with mentor. Discussion about dataset and project.	JOHARI ABDULLAH @ YAP GUAN KHENG (JOHARI YAP)19-Jul-2022 15:28:21
2	08-Apr-2022, Friday	18:00 - 18:30 (00:30)	Discussion with the supervisor. First meeting What are the requirements of the project? How we are going to do it. What should we avoid? Briefing.	JOHARI ABDULLAH @ YAP GUAN KHENG (JOHARI YAP)11-May-2022 08:46:12
3	09-Apr-2022, Saturday	19:00 - 22:00 (03:00)	Studied about deep learning. Implementation and basics of DL. Meeting with mentor on dataset and deep learning application	JOHARI ABDULLAH @ YAP GUAN KHENG (JOHARI YAP)19-Jul-2022 15:28:21
4	10-Apr-2022, Sunday	12:00 - 17:00 (05:00)	Started coding practice in deep learning. Read articles about deep learning techniques.	JOHARI ABDULLAH @ YAP GUAN KHENG (JOHARI YAP)19-Jul-2022 15:28:21
5	22-Apr-2022, Friday	14:00 - 14:30 (00:30)	Discussion about dataset with mentor.	JOHARI ABDULLAH @ YAP GUAN KHENG (JOHARI YAP)19-Jul-2022 15:28:21
6	22-Apr-2022, Friday	15:30 - 16:30 (01:00)	Meeting with the supervisor. Suggestion on implementation and report writing. discussing about deep learning and confusions	JOHARI ABDULLAH @ YAP GUAN KHENG (JOHARI YAP)19-Jul-2022 15:28:21
7	23-Apr-2022, Saturday	11:00 - 18:30 (07:30)	Meeting with mentor. Practiced coding. Read and watched tutorial on how to work with different models. Doubt clearance, some more doubts now.	JOHARI ABDULLAH @ YAP GUAN KHENG (JOHARI YAP)19-Jul-2022 15:28:21
8	29-Apr-2022, Friday	15:30 - 16:30 (01:00)	Got the data from mentor. Discussion about folder structure. got to about the images to use in model	JOHARI ABDULLAH @ YAP GUAN KHENG (JOHARI YAP)19-Jul-2022 15:28:21
9	08-May-2022, Sunday	13:30 - 19:00 (05:30)	Meeting with supervisor, mentor. studied about transforming dataset from dcm to jpg. applying transformation on python.	JOHARI ABDULLAH @ YAP GUAN KHENG (JOHARI YAP)19-Jul-2022 15:28:21

10	12-May-2022, Thursday	16:30 - 17:00 (00:30)	Discussion about new proposal, Data understanding	JOHARI ABDULLAH @ YAP GUAN KHENG (JOHARI YAP)19-Jul-2022 15:28:21
11	13-May-2022, Friday	15:00 - 23:30 (08:30)	Worked on new proposal. Send to mentor for approval.	Very hardworking JOHARI ABDULLAH @ YAP GUAN KHENG (JOHARI YAP)19-Jul-2022 15:28:21
12	20-May-2022, Friday	18:00 - 19:30 (01:30)	Midterm presentation. Discussion about changing some objectives and finding public datasets.	JOHARI ABDULLAH @ YAP GUAN KHENG (JOHARI YAP)19-Jul-2022 15:28:21
13	25-May-2022, Wednesday	15:00 - 17:30 (02:30)	Discussed about new dataset. On finding new objectives. Took approval from mentor in the meeting. Discussed with the supervisor.	JOHARI ABDULLAH @ YAP GUAN KHENG (JOHARI YAP)19-Jul-2022 15:28:21
14	29-May-2022, Sunday	15:30 - 17:00 (01:30)	Reported mentor about finding and difficulties.	JOHARI ABDULLAH @ YAP GUAN KHENG (JOHARI YAP)19-Jul-2022 15:28:21
15	30-May-2022, Monday	11:30 - 13:00 (01:30)	Meeting with supervisor. Discussed about difficulties. Read about some references. Started report writing	JOHARI ABDULLAH @ YAP GUAN KHENG (JOHARI YAP)19-Jul-2022 15:28:21
16	04-Jun-2022, Saturday	14:30 - 23:30 (09:00)	Continued working on project. Deep learning model taking much time to run. Getting errors. Reported to mentor.	JOHARI ABDULLAH @ YAP GUAN KHENG (JOHARI YAP)19-Jul-2022 15:28:21
17	07-Jun-2022, Tuesday	20:00 - 23:30 (03:30)	Continued working on project. Wrote report. Read some of the articles and journals. Watched some tutorials.	JOHARI ABDULLAH @ YAP GUAN KHENG (JOHARI YAP)19-Jul-2022 15:28:21
18	10-Jun-2022, Friday	16:00 - 16:30 (00:30)	Meeting with mentor.	JOHARI ABDULLAH @ YAP GUAN KHENG (JOHARI YAP)19-Jul-2022 15:28:21
19	11-Jun-2022, Saturday	11:30 - 12:30 (01:00)	Meeting with supervisor. Continued working on project.	JOHARI ABDULLAH @ YAP GUAN KHENG (JOHARI YAP)19-Jul-2022 15:28:21
20	14-Jun-2022, Tuesday	13:00 - 23:30 (10:30)	Continued working on project. Sequential started giving accuracy. Reported to mentor and supervisor.	JOHARI ABDULLAH @ YAP GUAN KHENG (JOHARI YAP)19-Jul-2022 15:28:21
21	19-Jun-2022, Sunday	14:00 - 18:30 (04:30)	Changing parameters. Data augmentation application. Error in model. Changes and modification.	JOHARI ABDULLAH @ YAP GUAN KHENG (JOHARI YAP)19-Jul-2022 15:28:21

22	22-Jun-2022, Wednesday	18:00 - 23:30 (05:30)	Parameter tuning. accuracy and validation both working nicely. report writing. journal reading. reported scores to mentor and supervisor.	JOHARI ABDULLAH @ YAP GUAN KHENG (JOHARI YAP)19-Jul-2022 15:28:21
23	28-Jun-2022, Tuesday	10:30 - 18:30 (08:00)	Transfer Learning. Finding pretrained weights.	JOHARI ABDULLAH @ YAP GUAN KHENG (JOHARI YAP)19-Jul-2022 15:28:21
24	30-Jun-2022, Thursday	14:30 - 18:00 (03:30)	Hyperparameter tuning. Model changing. Report writing.	JOHARI ABDULLAH @ YAP GUAN KHENG (JOHARI YAP)19-Jul-2022 15:28:21
25	01-Jul-2022, Friday	14:00 - 14:30 (00:30)	Meeting with mentor. Brief about what has been done.	JOHARI ABDULLAH @ YAP GUAN KHENG (JOHARI YAP)19-Jul-2022 15:28:21
26	03-Jul-2022, Sunday	14:00 - 17:30 (03:30)	Report writing. Transfer learning accuracy 100%	JOHARI ABDULLAH @ YAP GUAN KHENG (JOHARI YAP)19-Jul-2022 15:28:21
27	07-Jul-2022, Thursday	19:00 - 23:30 (04:30)	Assembled the code and run again to find any broken thing. Reported to mentor, supervisor.	JOHARI ABDULLAH @ YAP GUAN KHENG (JOHARI YAP)19-Jul-2022 15:28:21
28	17-Jul-2022, Sunday	13:00 - 20:00 (07:00)	Meeting with mentor, supervisor. Showcased the work. checked prediction and model prediction speed. Report writing.	Good effort JOHARI ABDULLAH @ YAP GUAN KHENG (JOHARI YAP)19-Jul-2022 15:28:21
29	18-Jul-2022, Monday	12:30 - 15:00 (02:30)	Meeting with mentor. meeting with supervisor. Final approval. Report finish.	JOHARI ABDULLAH @ YAP GUAN KHENG (JOHARI YAP)19-Jul-2022 15:28:21